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Impact of Risk Perception and Emotional Influence on Gen Z's Decision-Making in Life Insurance Policy Purchasing Intent.

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ABSTRACT -

This study investigates the impact of emotional intelligence and risk perception on Generation Z's decision-making in purchasing life insurance policies, specifically within the Indian context. Gen Z, being digitally savvy and emotionally aware, evaluates financial products not just through logic but also through emotional and psychological factors. The research addresses a gap in behavioral finance by focusing on how emotional influence and subjective financial knowledge shape insurance attitudes and purchase intentions among younger consumers. Using a quantitative approach, data were collected from 299 Gen Z respondents via online surveys and analyzed using SmartPLS. The study examined relationships between Emotional Intelligence (EI), Risk Perception (RP), Attitude Toward Insurance (ATI), and Purchase Intention (PI). Results revealed that EI significantly affects RP and ATI, while RP positively influences ATI, which in turn drives PI. Emotional Intelligence indirectly influences purchase intention through both RP and ATI, highlighting the mediating roles of perception and attitude. The findings suggest that Gen Z's insurance choices are driven by emotional and perceptual considerations, not solely rational thought. Insurers should design emotionally intelligent, personalized strategies to better connect with this demographic. This research contributes to a deeper understanding of behavioral finance and supports the development of inclusive financial products for emerging markets like India.

INDEX TERMS –

- Risk Perception
- Life Insurance Decision Making
- Behavioral Finance
- Emotional Influence
- Purchase Intent

INTRODUCTION:

The integration of behavioral finance into the life insurance industry presents a transformative opportunity to reshape how products are designed, marketed, and consumed—particularly for Generation Z (Gen Z). This digitally native, socially conscious, and emotionally aware generation is redefining the expectations for financial services. As Gen Z emerges as a significant economic force, insurers must understand the emotional and psychological frameworks that guide their financial decision-making.

Unlike previous generations who often viewed life insurance as a rational financial safeguard or a product of institutional trust, Gen Z seeks transparency, personalization, and digital convenience. Their decisions are influenced by emotional drivers such as financial anxiety, fear of instability, and cognitive biases like loss aversion. This shift highlights the need for insurers to create emotionally engaging and personalized insurance solutions that align with Gen Z's values and expectations.

Positioning life insurance not merely as a safety net, but as a tool for long-term security, wealth creation, and intergenerational impact can reshape how Gen Z perceives it. If insurers educate young consumers about the broader benefits of life insurance, they can build stronger engagement. Gen Z's values around sustainability, wellness, and ethical investing also offer avenues for product innovation. Features like wellness incentives, mental health coverage, and flexible premium structures could align with their holistic life goals.

Insurers that respond to these shifts stand to gain long-term customer loyalty by designing offerings that resonate with Gen Z's emotional landscape. Traditional insurance models based purely on rational pricing and policy features fall short in capturing the affective drivers of Gen Z's behavior. By understanding the roles of trust, emotion, and perceived control in purchasing decisions, insurers can better connect with this skeptical yet value-driven generation.

Existing literature in behavioral finance provides insights into how emotional and cognitive biases shape financial decisions, yet research specific to Gen Z and life insurance remains sparse. Studies typically focus on investment behavior or older demographics, overlooking how Gen Z's digital habits and emotional responses influence their insurance decisions. This gap signals a need for further research into how perceived financial knowledge—often shaped by social media and peer influence—impacts Gen Z's decision-making processes.

Moreover, digital experiences now play a central role in how Gen Z interacts with insurance providers. Personalized communication, emotional storytelling, and trust-building mechanisms on digital platforms are becoming essential. Understanding these behavioral cues is critical to enhancing user experience and building enduring relationships with younger consumers.

Policy lapses, particularly among young policyholders, are often attributed to cost or product-related issues. However, emotional disengagement or dissatisfaction may be equally responsible. Addressing these emotional factors can help insurers reduce lapse rates and improve product retention.

Ultimately, bridging behavioral finance and life insurance offers mutual benefits. Gen Z gains access to products that are better aligned with their emotional needs and financial goals, while insurers can build deeper connections and more sustainable customer relationships. Policymakers, too, can use these insights to craft more effective financial education and inclusion strategies. By integrating behavioral principles, the life insurance industry can evolve into a more empathetic, relevant, and future-ready sector.

LITERATURE SURVEY:

The integration of behavioral finance and life insurance decision-making has garnered significant academic attention, revealing how cognitive biases, emotional influences, and socio-economic factors shape financial behavior. Traditional economic models, such as the Efficient Market Hypothesis (EMH), assume rational decision-making by investors and policyholders (Fama, 1970). However, empirical research demonstrates that psychological factors often lead to suboptimal financial choices (Brighetti et al., 2014). This paper synthesizes key findings from behavioral finance, insurance adoption, risk perception, and policyholder behavior, providing a coherent and comprehensive overview of the field.

Behavioral finance challenges the traditional rational actor model by incorporating insights from psychology and neuroscience. Brighetti et al. (2014) argue that emotions and cognitive biases—such as overconfidence, loss aversion, and framing effects—significantly distort financial decisions. Their neuroeconomic research highlights the role of the amygdala in processing fear and risk, while the prefrontal cortex regulates decision-making. Individuals with impaired emotional regulation tend to exhibit higher financial risk-taking behaviors, underscoring the need for interventions that mitigate cognitive biases in financial education and policy (Brighetti et al., 2014). Similarly, Almansour et al. (2023) identify herding behavior, the disposition effect, and blue-chip bias as key psychological influences on investment decisions. Herding behavior occurs when investors follow market trends rather than conducting independent analysis, often leading to asset bubbles or crashes (Shiller, 2000). The disposition effect refers to the tendency to sell winning investments prematurely while holding onto losing ones, driven by loss aversion (Kahneman & Tversky, 1979). Blue-chip bias describes investors' preference for well-established companies, even when financial performance does not justify it (Almansour et al., 2023). Overconfidence, however, directly impacts investment choices without necessarily altering risk perception, suggesting that overconfident investors may disregard objective risk assessments (Barber & Odean, 2001).

Financial literacy plays a moderating role in mitigating behavioral biases. Diacon (2004) finds that investors with higher financial literacy demonstrate better risk management and more informed decision-making. However, psychological biases persist even among financially literate individuals, necessitating targeted educational interventions (Lusardi & Mitchell, 2014). Lim et al. (2018) further differentiate between objective financial knowledge (factual understanding) and subjective financial knowledge (self-perceived competence). Their study reveals that subjective knowledgably influences investment intentions than objective knowledge, implying that confidence in one's financial understanding—regardless of its accuracy—drives behavior more than actual expertise (Lim et al., 2018). Effective risk communication is another critical factor in financial decision-making. Fischhoff (2002) emphasizes that experts and laypersons perceive risks differently due to cognitive heuristics, such as availability bias (relying on readily available information) and anchoring (over-relying on initial information). Tailoring risk communication to address these biases can improve decision-making (Fischhoff, 2002). Mitchell (1995) extends this discussion to organizational contexts, identifying six types of risk—financial, performance, physical, social, psychological, and time-related—and advocating for strategies such as diversification, expert consultation, and procedural safeguards to mitigate them (Mitchell, 1995).

Life insurance decisions are similarly influenced by behavioral factors. Tennyson (2014) demonstrates that past financial experiences shape risk tolerance: individuals who have endured economic crises tend to adopt conservative insurance strategies, while those with financial stability exhibit greater risk-taking tendencies. Demographic variables, including age, income, and education, further moderate these effects, with financial literacy reducing the impact of cognitive biases (Tennyson, 2014). In India, Ramalingam and Venkatesan (2023) examine Unit-Linked Insurance Products (ULIPs) using a cognitive model that incorporates risk perception, financial literacy, and trust. Their structural equation modeling (SEM) analysis of 480 investors reveals that financial literacy enhances rational decision-making, whereas risk perception deters investment. Post-purchase cognitive dissonance—a psychological discomfort arising from conflicting beliefs—often leads to buyer's remorse, highlighting the need for transparent communication and investor education (Ramalingam & Venkatesan, 2023).

Nair and Vineeth (2019) investigate financial anxiety among Indian salaried workers, finding moderate anxiety levels and significant underinsurance (only 13.3% had adequate life insurance coverage). Financial anxiety correlates with extreme income levels and younger age groups but not gender, suggesting that emotional factors—such as fear of financial instability and familial responsibility—drive insurance purchases (Nair & Vineeth, 2019). The Indian life insurance sector faces structural challenges, including low penetration (2.72%) and density ($47), despite regulatory reforms such as the Insurance Regulatory and Development Authority (IRDA) Act of 1999 (Radhika & Satuluri, 2019). Ghosh (2013) attributes growth barriers to digitalization gaps, while Dash (2018) identifies rural-urban disparities in awareness and affordability. Ankitha and Basri (2019) emphasize the role of relational selling, where agent transparency and trust-building are critical to reducing mis-selling and enhancing policyholder confidence (Ankitha & Basri, 2019). Macroeconomic factors also influence life insurance demand. Mathew and Sivaraman (2017) analyze data from 1980 to 2014, finding that financial sector development and inflation positively impact insurance uptake, whereas higher real interest rates and income exhibit negative relationships. Their study suggests that expanding financial inclusion and reducing barriers to insurance adoption could enhance market growth (Mathew & Sivaraman, 2017). Nagaraja (2015) notes a decline in new policy growth, urging product innovation and regulatory reforms to strengthen competition between public and private insurers (Nagaraja, 2015). Lapse risk—the termination of policies before maturity—poses significant challenges for insurers. Eling and Kochanski (2012) review over 50 studies on lapse behavior, highlighting its implications for liquidity and profitability. Policyholders may lapse due to financial distress or better alternatives, with dynamic models providing more accurate predictions than static approaches (Eling & Kochanski, 2012). Gatzert (2009) examines implicit options in life insurance contracts, such as surrender options and interest rate guarantees. Regulatory frameworks like Solvency II have encouraged insurers to adopt modular products (e.g., variable annuities) that improve transparency and risk management (Gatzert, 2009). Villeneuve (2000) applies microeconomic theory to life insurance, emphasizing the bequest motive—the desire to leave financial security for heirs—as a key driver of demand. Contract theory further explains how insurers balance flexibility and opportunistic behavior through features like surrender charges and renewal options (Villeneuve, 2000). Liebenberg et al. (2011) use dynamic modeling to show that life events—such as marriage, parenthood, and unemployment—significantly influence policy ownership. New parents are more likely to purchase term insurance, while unemployed households often surrender whole life policies, supporting the emergency fund hypothesis (Liebenberg et al., 2011). Cowley and Cummins (2005) explore life insurance securitization, a financial innovation that enhances liquidity but faces regulatory complexities. Unlike traditional asset-backed securities, insurance securitization involves credit risk retention, limiting its adoption (Cowley & Cummins, 2005). Grosen and Jørgensen (1999) analyze participating policies, which offer guaranteed returns and periodic bonuses. These policies can be decomposed into three components: a risk-free bond, a bonus option, and a surrender option. Insurers must carefully balance guaranteed returns with reserve adequacy to avoid solvency risks (Grosen & Jørgensen, 1999). Bikker and Leuvensteijn (2008) assess competition in the Dutch life insurance market, finding weak demand-side competition due to product complexity and low consumer bargaining power. Regulatory measures to enhance transparency could improve market efficiency (Bikker & Leuvensteijn, 2008). Adem and Dagdeviren (2016) propose a hesitant fuzzy linguistic model to address uncertainty in policy selection. Their multi-criteria decision-making (MCDM) framework incorporates expert evaluations of factors such as insurer reliability, pricing, and customer service, improving decision accuracy (Adem & Dagdeviren, 2016).

The COVID-19 pandemic accelerated digital transformation in the insurance sector. Yadav and Suryavanshi (2021) report a 67.56% decline in traditional policy sales but a 30–40% surge in online purchases. Insurers adapted by leveraging digital tools, though challenges such as liquidity pressures and claims processing delays persisted (Yadav & Suryavanshi, 2021). Behavioral finance demonstrates that financial and insurance decisions are rarely fully rational, being significantly influenced by cognitive biases, emotional factors, and socio-economic contexts. Several key implications emerge from this understanding. First, enhancing financial literacy and education is crucial for helping individuals recognize and mitigate behavioral biases in their decision-making processes (Lusardi & Mitchell, 2014). Second, transparent communication between insurers and policyholders can help reduce cognitive dissonance and build trust, particularly in complex products like Unit-Linked Insurance Plans (Ramalingam & Venkatesan, 2023). Third, regulatory reforms are needed to address persistent issues like mis-selling practices while promoting digital inclusion to expand insurance access (Radhika & Satuluri, 2019). Finally, product innovation - such as the development of modular insurance policies with flexible features - can better align products with consumer risk profiles and needs (Gatzert, 2009). These insights collectively suggest that addressing behavioral factors requires a multi-pronged approach combining education, regulation, product design, and transparent industry practices to improve financial decision-making outcomes. Future research should explore the role of artificial intelligence (AI) in behavioral finance and the long-term effects of digital insurance platforms. Policymakers must prioritize consumer protection, financial education, and market stability to foster sustainable growth in the insurance sector.

METHODOLOGY:

Using SmartPLS and a quantitative research methodology is justified for this study as it involves examining measurable relationships between constructs such as Risk Perception, Emotional Influence, and Purchase Intent among Gen Z. Quantitative methods enable statistical validation, generalizability, and objective analysis of behavioral patterns (Creswell, 2014). SPSS facilitates efficient data handling, correlation, regression, and path analysis, making it ideal for exploring complex relationships and testing hypotheses (Pallant, 2020). Given the study's focus on numerical data from survey responses, this approach ensures methodological rigor and replicability, which are essential in understanding consumer decision-making in the insurance sector.

RESEARCH GAP:

The integration of behavioral finance into life insurance decision-making has significantly enhanced our understanding of consumer behavior, highlighting key psychological and emotional drivers such as cognitive biases, emotional intelligence (EI), and risk perception. However, significant gaps remain, particularly in relation to Generation Z (Gen Z) and in emerging markets like India.

A major gap is the underrepresentation of Gen Z in insurance-related behavioral finance research. Most existing studies focus on older adults with established financial responsibilities, overlooking the unique characteristics of Gen Z—digital literacy, social influence, and a post-pandemic risk mindset. As this cohort enters the workforce, there is a pressing need to understand how their emotional and cognitive responses differ in the context of life insurance decisions. Without targeted empirical data, insurers may struggle to design products and strategies that resonate with this generation.

Another gap lies in the over-reliance on rational decision-making models. While some studies contrast classical theories like utility theory with biases such as overconfidence or herding, few explore how these biases interact with emotional constructs like EI. This intersection remains underexplored, yet could provide a more nuanced understanding of high-stakes financial decisions. For instance, EI may not only affect risk perception but also influence post-purchase behaviors like policy continuation or regret, especially in emotionally volatile Gen Z consumers.

The geographic focus of behavioral insurance research is also skewed. In India, much of the literature focuses on macro issues like policy penetration or awareness, rather than micro-level psychological mechanisms. Given India's cultural diversity, low financial literacy, and emotional risk aversion, there is a need for behaviorally grounded, culturally sensitive research—particularly among Gen Z consumers. Emotional and psychological constructs like EI or subjective financial knowledge have yet to be adequately tested in Indian demographic samples.

Measurement and construct validity issues further complicate behavioral insurance research. Tools such as the Fornell-Larcker criterion and AVE are commonly used, but often yield weak outer loadings for abstract constructs like emotional influence, limiting model reliability. Improved scale development and validation are essential for accurate psychological profiling and predictive modeling.

Additionally, a disconnect exists between behavioral insights and practical product innovation. While some studies suggest flexible policy structures or modular plans, few link these innovations to specific behavioral traits. For example, how might high EI influence a consumer's preference for term vs. ULIP policies? Linking psychological factors to product design could enhance both customer satisfaction and market outcomes.

The rise of digital platforms in the insurance sector adds another dimension. Gen Z's digital-first behavior introduces new variables like online framing effects or reduced interpersonal trust. Yet, the behavioral consequences of digital insurance engagement remain underexplored. This is crucial for understanding how Gen Z evaluates policies and interacts with providers.

Finally, most studies neglect the post-purchase phase—policy lapse, renewal, or claims—which is often driven by emotional responses. Future research should adopt longitudinal and mixed-method approaches to trace emotional and cognitive changes across the policy lifecycle. Hybrid theoretical models integrating cognitive, emotional, and contextual factors can offer a more comprehensive understanding of life insurance behavior in the modern era.

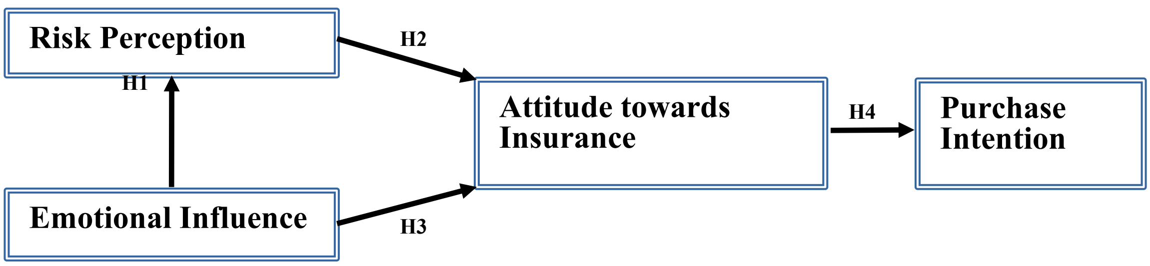
HYPOTHESES:

- **H1:** Emotional influence has a positive effect on Gen Z's perception of risk regarding life insurance.
- **H2:** Risk perception positively influences Gen Z's attitude towards life insurance.
- **H3:** Emotional influence positively affects Gen Z's attitude towards life insurance.
- **H4:** A positive attitude towards life insurance increases Gen Z's intention to purchase a life insurance policy.

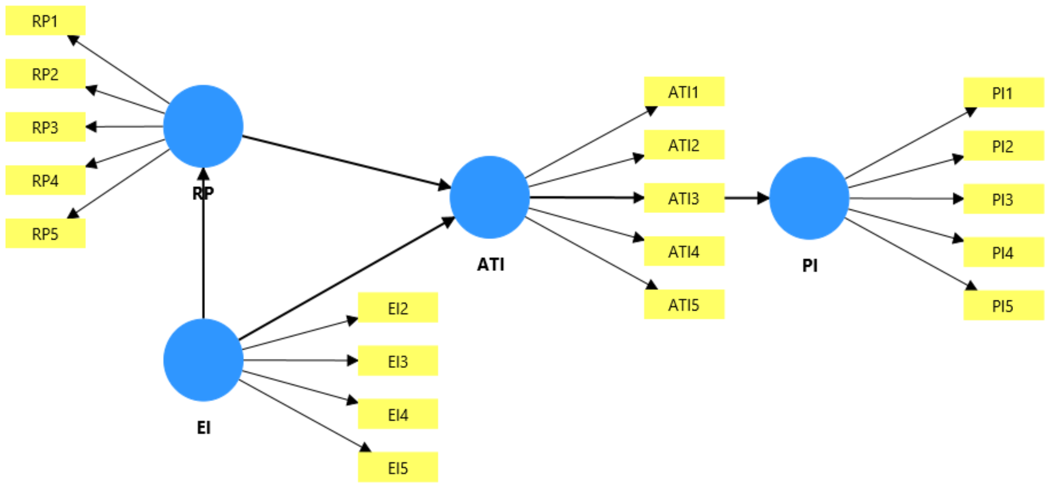
SAMPLE SIZE:

Convenience sampling is useful for this study as it allows quick and cost-effective access to a specific population—Gen Z respondents—who are often digitally active and responsive to online surveys. With a sample size of 299, it provides sufficient data to conduct meaningful statistical analysis while accommodating time and resource constraints (Etikan, Musa, & Alkassim, 2016). Although not fully representative, convenience sampling is appropriate for exploratory research like this, where the goal is to identify patterns and relationships rather than to generalize findings to a larger population.

FRAMEWORK:



ANALYSIS AND INTERPRETATION:



(Structured Equation Modeling)

Path Coefficients

Path Coefficients	
Path	**Path Coefficient (β)**
ATI -> PI	0.565
EI -> ATI	0.298
EI -> RP	0.704
RP -> ATI	0.436

The path coefficient analysis reveals key relationships among the studied constructs. Emotional Intelligence (EI) significantly influences Risk Perception (RP) (β = 0.704) and Attitude Toward Insurance (ATI) (β = 0.298). Additionally, RP has a positive effect on ATI (β = 0.436), indicating a mediating role. ATI, in turn, shows a strong influence on Purchase Intent (PI) (β = 0.565), establishing it as a critical determinant of consumer decision-making. These findings suggest that EI not only directly affects ATI but also indirectly influences it through RP, ultimately shaping PI. The model highlights the importance of psychological factors in consumer behavior.

Indirect effects and Total effects

Indirect effects	
Path	**Indirect Effect (β)**
EI -> ATI -> PI	0.322
RP -> ATI -> PI	0.519
EI -> RP -> ATI -> PI	0.436
EI -> RP -> ATI	0.307

Total effects	
Path	**Indirect Effect (β)**
ATI -> PI	0.356
EI -> ATI	0.605
EI -> PI	0.134

EI -> RP	0.704
RP -> ATI	0.436
RP -> PI	0.487

The indirect and total effects analysis underscores the mediating roles of Attitude Toward Insurance (ATI) and Risk Perception (RP). Emotional Intelligence (EI) significantly influences Purchase Intent (PI) through ATI (β = 0.322) and via the sequential path through RP and ATI (β = 0.436). RP also exerts a notable indirect effect on PI through ATI (β = 0.519). In terms of total effects, EI strongly impacts ATI (β = 0.605) and RP (β = 0.704), while ATI maintains a direct and indirect role in shaping PI (total β = 0.356). These findings confirm the centrality of EI and RP in consumer decision pathways.

Outer loading

Table Format for Outer loading	
Construct	**Outer Loading (β)**
ATI1 <- ATI	0.799
ATI2 <- ATI	0.799
ATI3 <- ATI	0.812
ATI4 <- ATI	0.716
ATI5 <- ATI	0.388
EI2 <- EI	0.874
EI3 <- EI	0.884
EI4 <- EI	0.827
EI5 <- EI	0.597
PI1 <- PI	0.921
PI2 <- PI	0.959
PI3 <- PI	0.909
PI4 <- PI	0.912
PI5 <- PI	0.909
RP1 <- RP	0.927
RP2 <- RP	0.910
RP3 <- RP	0.678
RP4 <- RP	0.346
RP5 <- RP	-0.209

The outer loading analysis assesses indicator reliability for each construct. Most items show acceptable loadings above the 0.70 threshold, indicating good convergent validity. For **Attitude toward Insurance (ATI)**, four indicators exceed 0.70, but **ATI5** is low (β = 0.388), suggesting potential removal. **Emotional Influence (EI)** indicators also load strongly, except **EI5** (β = 0.597), which is borderline. **Purchase Intention (PI)** demonstrates excellent indicator reliability, with all items above 0.90. **Risk Perception (RP)** shows mixed results: **RP1–RP3** are strong, while **RP4** (β = 0.346) and **RP5** (β = -0.209) fall below acceptable thresholds and may compromise construct validity.

Construct Reliability and Validity

Table Format for Construct Reliability and Validity				
Construct	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
ATI	0.754	0.797	0.837	0.520
EI	0.810	0.837	0.878	0.647
PI	0.956	0.956	0.966	0.850
RP	0.680	0.822	0.724	0.562

The assessment of construct reliability and validity shows satisfactory results. All constructs exhibit acceptable **Cronbach's alpha** values (≥ 0.70), except **Risk Perception (RP)** (α = 0.680), which is slightly below the threshold. **Composite reliability** (rho_c) for all constructs exceeds 0.70, confirming internal consistency. The **Average Variance Extracted (AVE)** values are all above the recommended minimum of 0.50, supporting convergent validity. **Purchase Intention (PI)** demonstrates the highest reliability (α = 0.956, AVE = 0.850), while **RP** presents the weakest metrics, suggesting the need for improvement in its measurement indicators. Overall, the constructs are valid and reliable for further analysis.

Discriminant Validity

Table Format for Discriminant Validity (Fornell-Larcker Criterion)				
Construct	**ATI**	**EI**	**PI**	**RP**
ATI	0.721			
EI	0.605	0.804		
PI	-0.089	0.441	0.922	
RP	0.646	0.704	0.255	0.680

The Fornell-Larcker criterion confirms discriminant validity, as each construct's square root of Average Variance Extracted (diagonal values) exceeds its correlations with other constructs. For instance, **Purchase Intention (PI)** shows the highest AVE square root (0.922), greater than its correlations with EI (0.441), ATI (-0.089), and RP (0.255). Similarly, **Emotional Influence (EI)** (0.804) and **Attitude toward Insurance (ATI)** (0.721) also fulfil this criterion. Although **Risk Perception (RP)** has a lower AVE value (0.680), it still surpasses its inter-construct correlations. These results support the distinctiveness of each construct, confirming that the model meets the requirements for discriminant validity.

DISCUSSION:

The findings of this study provide valuable insights into the interplay between Emotional Intelligence (EI), Risk Perception (RP), Attitude Toward Insurance (ATI), and Purchase Intent (PI). Path coefficient analysis reveals that EI significantly influences both RP (β = 0.704) and ATI (β = 0.298), emphasizing its foundational role in shaping psychological responses to purchase decisions. Additionally, RP positively affects ATI (β = 0.436), and ATI strongly drives PI (β = 0.565), highlighting the mediating chain that leads from internal emotional capacity to consumer action.

The indirect effects further underline this dynamic. EI impacts PI both directly (β = 0.134) and indirectly through ATI (β = 0.322) and via RP and ATI combined (β = 0.436). RP also plays a notable indirect role in influencing PI (β = 0.519). The total effects reinforce the significance of EI, with its strongest influence on RP (β = 0.704) and ATI (β = 0.605), and a meaningful, albeit smaller, impact on PI (β = 0.134). This affirms that consumer intent is not just a product of rational thought but is significantly mediated by psychological and perceptual factors.

Furthermore, the analysis of construct validity and reliability demonstrates sound measurement properties for most constructs. However, certain indicators for ATI and RP, such as ATI5 and RP5, underperformed and may require refinement. While PI indicators showed excellent reliability (AVE = 0.850), RP's lower Cronbach's alpha (α = 0.680) and weak outer loadings suggest the need for enhanced item development.

Overall, the model substantiates the integral role of EI in shaping consumer behavior through its influence on risk assessment and attitudinal disposition, providing theoretical and practical implications for marketing strategies and consumer psychology.

IMPLICATIONS FOR RESEARCH:

The results of this study offer important implications for future academic research. The strong influence of Emotional Intelligence (EI) on both Risk Perception (RP) and Attitude Toward Insurance (ATI) underscores the need to further explore EI as a central construct in consumer behavior models. Future research can delve deeper into the multidimensional nature of EI and how its individual components (e.g., emotional regulation, empathy) differentially impact consumer decisions. Additionally, the mediating roles of RP and ATI open avenues for extended models that incorporate other psychological or contextual variables, such as trust, brand reputation, or perceived value. Longitudinal studies may also be conducted to observe how these relationships evolve over time, particularly in high-involvement or risk-laden purchasing environments.

IMPLICATIONS FOR PRACTICE:

From a practical standpoint, marketers and business strategists should consider integrating emotional intelligence training and emotional cues into customer engagement efforts. Since EI indirectly influences Purchase Intent (PI) through RP and ATI, marketing campaigns should aim to foster positive attitudes and reduce perceived risks by building emotional connections and trust with consumers. For instance, messaging that emphasizes empathy, safety, and reliability can mitigate risk perception and improve consumer receptivity. Additionally, understanding the role of consumer attitudes allows companies to craft more targeted communication strategies that align with customer values and emotional drivers. In industries like insurance, finance, or healthcare—where risk perception is naturally high—tailored strategies based on these insights can significantly enhance purchase outcomes.

LIMITATIONS OF THE STUDY:

This study, while insightful, has certain limitations. Firstly, the reliance on self-reported measures may introduce bias, particularly in constructs like Emotional Intelligence and Risk Perception, which are inherently subjective. Secondly, some measurement items—such as ATI5 and RP5—demonstrated weak outer loadings, potentially compromising the robustness of those constructs. Additionally, the cross-sectional nature of the study restricts the ability to infer causality among the variables. The relatively low Cronbach's alpha for Risk Perception ($\alpha = 0.680$) also suggests limited internal consistency. Lastly, the model may not fully capture external factors like cultural context or socio-economic influences on consumer purchase behavior.

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