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Gender Differences in Neural Decision-Making: Cognitive Mechanisms, Educational Implications, and the Role of AI

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Abstract: *This narrative review synthesises evidence on gender-specific neurocognitive mechanisms underlying decision-making, emotional processing, and learning, and examines how AI-driven analyses can enhance personalised interventions. Drawing on EEG, fMRI, MEG, ERP, and eye-tracking studies, we show that women preferentially engage medial prefrontal and limbic networks, during semantic-relational and emotional tasks, whereas men recruit parietal-occipital circuits for visuospatial processing. Cultural context further shapes these patterns. AI applications, such as machine learning classifiers on neurophysiological data, improve the accuracy of gender-informed predictions, and support adaptive, neurodiversity-aware pedagogies. We conclude that integrating neuroscientific and AI insights can inform gender-sensitive educational design and decision-support systems, provided ethical safeguards against algorithmic bias and privacy breaches are in place.*

Keywords: *educational implications; cognitive mechanisms; gender differences; decision-making; emotional processing; cultural influences; fMRI; EEG; MEG; artificial intelligence; targeted advertising.*

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1. Introduction

Neuroscience offers novel approaches to understanding a wide array of human behavioural patterns, including consumer decision-making processes. Among its notable interdisciplinary contributions is the enhancement of our cognitive insight of how advertising influences potential consumers. Neuromarketing, more accurately termed *Consumer Neuroscience*, emerged from the convergence of neuroscience and marketing (Morin, 2011). Initially developed by Gerald Zaltman, this field seeks to understand how marketing stimuli impact brain function, leveraging psychological data to optimise advertising strategies (Lee, Broderick, & Chamberlain, 2007).

As an emerging discipline, neuromarketing integrates knowledge from psychology, neuroscience, and behavioural economics (Gurgu, Gurgu, & Tonis, 2020). Its central pursuit is to decode the neural mechanisms that guide product identification, evaluation, and purchase behaviour. Although commercial interests often drive research in this field, peer-reviewed studies have revealed reproducible neurocognitive patterns activated in response to advertising stimuli (Morin, 2011). Corporate interest in neuromarketing is largely underpinned by two core assumptions (Ariely & Berns, 2010). First, neural data is thought to reveal unconscious preferences, thereby offering insights beyond traditional self-report methods, which may not reliably predict actual purchasing behaviour. Secondly, neuroimaging technologies are perceived as tools to anticipate market performance early in the product development cycle, potentially reducing investment risks.

Despite these advantages, the application of neuromarketing raises significant ethical and methodological concerns (Fisher, Chin, & Klitzman, 2010). Inter-institutional collaborations often blur the line between scientific rigour and commercial objectives, and the absence of standardised data collection protocols challenges the field's transparency. There is a growing consensus on the need for interdisciplinary dialogue to prevent misuse and ensure that neurotechnological findings are communicated responsibly.

A particularly salient area of investigation in consumer neuroscience involves gender-based differences in cognitive-affective dynamics. Research indicates that males and females differ in neurophysiological reactivity to various stimuli, including facial expressions, colours, social interactions, and branding cues (Proverbio, 2019). These distinctions stem from hormonal, structural, and functional variations in the brain, which also manifest in divergent consumer behaviours. For instance, women often exhibit greater sensitivity to emotionally charged advertisements, whereas men may respond more to visually dynamic or functionally informative stimuli (Shahrajabian et al., 2023).

Recognising these sex-based neurobiological and psychological differences is essential for refining both marketing strategies and our comprehensive model of consumer behaviour. Tools like EEG and eye-tracking technologies offer valuable insights into how these differences shape decision-making in real time, enhancing the granularity and relevance of neuromarketing research.

In parallel, artificial intelligence (AI) has emerged as a powerful analytic tool in neuromarketing. AI facilitates deeper analyses of neurophysiological datasets, identifying latent patterns that can inform the development of more personalised advertising approaches. Particularly, AI's capacity to account for cultural and gender diversity enables the design of inclusive and adaptive marketing strategies (Huang & Rust, 2021; Davenport et al., 2020).

This review aims to synthesise current findings on gender-specific neurocognitive mechanisms influencing decision-making and learning, examining how emotional processing, neural activation, and perceptual preferences vary by gender, and how these insights, when integrated with AI technologies, can enhance the precision and inclusivity of both modern marketing campaigns and gender-sensitive educational strategies.

2. Materials and Methods

This narrative literature review focuses on gender differences in decision-making and the underlying cognitive mechanisms, while examining the educational implications and the role of AI. To identify relevant sources, scientific databases (PubMed, Web of Science, Google Scholar) were

searched using terms such as “gender differences AND decision making”, “gender AND neuroimaging”, “cognitive mechanisms AND decision-making”, “educational neuroscience and gender”, and “AI AND neuromarketing”. Empirical studies and reviews published up to 2025, in English, that address gender differences from neurobiological and behavioural perspectives in decision-making were selected. The analysis is based on cognitive and neuroscientific models of decision-making, such as dual-process (cognitive-affective) models and brain reward circuits. The methodological approach is narrative synthesis: the identified literature was comparatively integrated, highlighting experimental results from neuroimaging studies (fMRI, EEG) and behavioural tests, as well as recent advances in the use of AI methods in neuromarketing and cognitive neuroscience. A rigid systematic framework (e.g., PRISMA) was not used, but a critical interpretative synthesis was performed, highlighting key theoretical concepts and emerging perspectives from the research.

3. Results

3.1 Neuroimaging Techniques

A variety of neuroimaging and physiological methods have been used to probe gender differences in decision-making. Functional magnetic resonance imaging (fMRI) offers high spatial resolution to identify active brain regions, though it has slower temporal dynamics (Morin, 2011). Electroencephalography (EEG) and magnetoencephalography (MEG) provide milliseconds of timing of neural responses, useful for tracking rapid decision processes (Vecchiato et al., 2011). Event-Related Potentials (ERPs), derived from EEG, reveal the time course of cognitive and emotional evaluation of stimuli (Hajcak et al., 2012). Table 1 summarises major neuromarketing techniques (e.g., fMRI, EEG, eye-tracking, ERPs) along with their primary functions, advantages, and limitations. For example, Table 1 shows that fMRI captures deep structures like the amygdala, but is costly and slow, whereas EEG/ERPs offer precise timing of attentional and emotional processes, but with lower spatial precision. AI-based analytics (machine learning, pattern recognition) are increasingly applied to these datasets to decode subtle gender-specific activation patterns (Huang & Rust, 2021; Davenport et al., 2020). Table 1 summarises these techniques along with their primary functions, advantages, and limitations.

Table 1. Neuromarketing Techniques and Their Applications

Technique	Function	Advantages	Limitations
fMRI	Measures cerebral blood flow to analyse brain activity (Morin, 2011).	High spatial resolution; detects deep brain structures (amygdala, nucleus accumbens).	Limited temporal resolution; expensive and stationary.
EEG	Records electrical activity from the cortex (Vecchiato et al., 2011).	High temporal resolution (millisecond accuracy); portable and cost-effective.	Low spatial resolution; primarily captures cortical activity.
MEG	Measures magnetic fields generated by neural activity (Vecchiato et al., 2011).	High spatial and temporal resolution; precise mapping of brain function.	Expensive; requires specialised facilities and shielding.

Eye Tracking	Analyses gaze patterns and visual attention in real-time (Vecchiato et al., 2011).	Provides insights into ad effectiveness and consumer engagement.	Does not directly measure neural processing.
ERPs (Event-Related Potentials)	Captures time-locked electrophysiological responses to stimuli (Hajcak et al., 2012).	Highly sensitive to emotional and cognitive engagement.	Requires extensive post-processing and analysis.
AI Analytics	Uses machine learning algorithms and deep learning techniques to analyse neuroimaging data (Huang & Rust, 2021).	Enables rapid processing of large datasets and facilitates personalised campaign	Dependence on data quality.

3.2. Brain Activity Related to Decision-Making and Emotional Processing

Key cortical and subcortical regions mediate decision-making. The prefrontal cortex (PFC), especially the ventromedial (vmPFC) and orbitofrontal (OFC) areas, integrates cognitive and affective information to evaluate risk and reward (Bechara, Damasio, & Damasio, 2000; Wallis, 2007). Damage to vmPFC impairs judgement and emotion-guided choices. The amygdala processes emotional salience and memory, interacting with PFC to balance emotion-cognition trade-offs (Phelps & LeDoux, 2005). The insula provides interoceptive awareness, linking bodily states to emotional experience (Craig, 2009). Basal ganglia circuits, including the ventral striatum, monitor rewards and prediction errors, influencing reinforcement learning. In addition, dopaminergic modulation (midbrain to PFC and basal ganglia) regulates motivation and expectation (O’Doherty et al., 2003). Table 2 lists these regions and their core functions in decision contexts (e.g., reward evaluation, emotional learning).

Table 2. Key Brain Regions Involved

Cerebral region	Key functions, Processes and Associated Mechanisms	References
Prefrontal Cortex (PFC)	The PFC, particularly the ventromedial prefrontal cortex (vmPFC) and orbitofrontal cortex (OFC), is crucial in decision-making and emotion regulation. The vmPFC integrates cognitive and emotional inputs to assess risks and rewards, decision outcomes. Studies have shown that damage to the vmPFC can impairs emotional and social functioning judgement and decision-making capabilities (Bechara, Damasio, & Damasio, 2000). The OFC is similarly involved in evaluating reward contingencies and modulating behavioural responses (Wallis, 2007).	(Bechara, Damasio & Damasio, 2000; Wallis, 2007)
Amygdala	The amygdala is critically involved in handling emotional responses, especially in situations involving fear and reward. It is pivotal for emotional learning and memory, as well as for modulating responses to emotionally salient	(Phelps & LeDoux, 2005)

	stimuli. Research shows that the amygdala interacts with the PFC to balance emotional responses and regulate decision-making (Phelps & LeDoux, 2005).
Insula	The insula is implicated in interoceptive awareness, allowing individuals to perceive and process bodily states associated with emotional experiences. This region is particularly important in empathy, emotional self-awareness, and decision-making by integrating visceral signals into cognitive processes (Craig, 2009).
Basal ganglia	The basal ganglia, particularly the ventral striatum, is integral to reward processing and reinforcement learning. It plays a role in anticipating and evaluating rewards, which directly influences decision-making processes. Activity in the ventral striatum has been linked to decisions based on reward prediction errors (O'Doherty et al., 2003).

Neural mechanisms such as the somatic marker hypothesis (Damasio's models) illustrate how interoceptive feedback signals guide advantageous choices (Bechara, Damasio & Damasio, 2000). For instance, anticipated loss aversion may engage the insula response, whereas reward anticipation engages striatal circuits. Disruptions in these circuits underlie maladaptive decisions (e.g., addiction). Overall, effective decision-making relies on a distributed network (PFC, amygdala, insula, basal ganglia) that integrates facts, context, and feelings (Bechara, Damasio & Damasio, 2000; O'Doherty et al., 2003).

3.3. Gender Differences in Decision Strategies

Extensive studies reveal that males and females often employ different cognitive and neural strategies when evaluating options and making decisions (summarised in Table 3). For example, women tend to engage in semantic and relational memory strategies and show heightened responses to emotional and social content. In contrast, men often rely on spatial and visual processing strategies, focusing on functional or aesthetic features (Meyers-Levy & Loken, 2015; Yoon et al., 2006). These tendencies emerge in various tasks ranging from product choice to navigation. Table 3 (Gender Differences in Decision-Making and Consumer Behaviour) explicitly contrasts female and male patterns: women show stronger medial prefrontal cortex (PFC) and hippocampal engagement for verbally rich information, whereas men show greater parietal and occipital activation for visuospatial cues. Behaviourally, females often prefer detailed, emotionally evocative information, whereas males prefer minimalist performance-oriented attributes.

Table 3. Gender Differences in Decision-Making and Consumer Behaviour

Aspect	Females	Males
Neural Processing	Engage in semantic and relational memory strategies (McCarthy et al., 1997).	Utilise spatial and visually-oriented strategies (Gron et al., 2000).

Decision-Making	More influenced by emotional and social appeals (Meyers-Levy & Loken, 2015).	Respond more strongly to functional and visually stimulating cues (Yoon et al., 2006).
Product Preference	Prefer aesthetically pleasing, detailed, and emotionally evocative designs (Meyers-Levy & Loken, 2015).	Favour minimalistic, functional, and performance-based product attributes (Yoon et al., 2006).
Emotional Engagement	Higher sensitivity to emotionally rich content, processed via the left frontal cortex (Davidson, 2004).	Stronger responses to spatial and action-oriented content, linked to right frontal cortex activity (Killgore & Yurgelun-Todd, 2007).
Attention to Ads	Maintain attention longer on relational and narrative-driven content (Cahill et al., 2001).	Prefer high-impact, visually dynamic, and action-focused stimuli (Andreano & Cahill, 2009).

These differences extend to attentional and emotional responses. Neurophysiological measures indicate that females allocate attention longer to narrative or relational ads, while males fixate more on high-impact visual stimuli (Davidson, 2004). Event-related potentials such as the N1 and P2 components differ by gender: females exhibit larger early (N1) and evaluative (P2) amplitudes to social/emotional images, reflecting greater motivational salience (Schupp et al., 2003; Meyers-Levy & Loken, 2015). Likewise, frontal EEG asymmetry shows sex-specific patterns: women display greater left frontal activation associated with approach-related, positive affect, while men exhibit stronger right frontal activity, linked to analytic and spatial processing (Davidson, 2004).

In sum, males and females deploy overlapping cognitive systems, but with biases towards different informational cues.

3.4. Memory and Attention

Memory encoding and sustained attention also exhibit gender-specific characteristics. During learning tasks, women typically exhibit stronger prefrontal and hippocampal activation, consistent with verbal/semantic encoding strategies (Cahill et al., 2001). This often yields better recall of verbal or narrative content. Men, conversely, engage more occipito-parietal regions during memorisation, reflecting reliance on imagery and spatial features (Gron et al., 2000). In attention tasks, females maintain focus longer on context-rich or socially relevant stimuli, whereas males respond more strongly to dynamic or novel stimuli. These patterns may be related to differential activation of attentional networks (e.g., the default mode vs. dorsal networks) (Mather & Lighthall, 2012).

3.5. Integration of AI Analytics

Machine learning and deep learning significantly enhance our ability to detect gender-specific neural signatures. For example, AI models trained on EEG power spectra can classify positive vs. negative product attitudes with up to 98% accuracy (Golnar-Nick, Farashi, & Safari, 2019; Mashrur et al., 2022). Functional near-infrared spectroscopy (fNIRS) combined with pattern-classification algorithms reveals that women from collectivist cultures show increased left dIPFC activation to family-oriented advertisements, whereas men from individualist cultures

respond more to performance-oriented messages (Duan et al., 2021; Basev, 2021). Such AI-driven approaches enable precise, real-time modelling of decision processes, integrating neural, behavioural, and demographic data (Nadanyiová, Gajanová, & Majerová, 2023; Stefko et al., 2021).

3.6. Cultural and Contextual Modulators

Culture and context modulate gender-related neural responses. In collectivist societies, both genders may prioritise relational and family-oriented cues; in individualistic contexts, personal achievement and autonomy are emphasised (Chiu & Hong, 2007; Han & Northoff, 2008). For example, Western women engage more with individualised narratives, whereas Eastern women prefer community-oriented themes. Men in Western cultures tend to favor innovation-focused content, while Eastern men may respond more to practical messages (Chiu & Hong, 2007). These effects involve regions like the medial PFC (self-related processing) and are captured by neuroimaging (Park & Gutchess, 2006).

3.7. Practical Applications and Tables

The combined insights have direct practical applications. Table 1 (above) enumerates neuromarketing tools that measure these effects. Table 2 (above) lists critical brain regions tied to decision and emotion. Table 3 (above) summarises gender differences in cognitive and neural processing during choice behaviour. Together, these tables guide both research and practice. For example, educators designing STEM materials might emphasise spatial visualisation for boys and verbal-contextual framing for girls, reflecting the neural biases described (Mulvey, Miller, & Rizzardi, 2017). In marketing or product design, campaigns targeting women might use empathetic storytelling, whereas for men highlight functional visuals.

By tailoring strategies to neural and cognitive profiles, interventions become more effective. For instance, adaptive learning platforms could use EEG or eye-tracking feedback (Table 1) to modulate content delivery in real time. However, all such applications should be informed by robust cognitive models and ethical oversight.

4. Discussion

This comprehensive review demonstrates how biological sex shapes decision-related neural mechanisms and highlights implications beyond marketing, notably in education and behaviour modelling.

4.1. Educational Implications

The documented sex differences in cognition suggest that teaching strategies could be gender-sensitive. For example, girls' relative strength in semantic and emotional processing implies that language-rich, narrative-based learning might enhance engagement for female students (Cahill et al., 2001; Davidson, 2004). Boys' preferences for spatial and action-oriented processing suggest benefits from visual-spatial and hands-on problem-solving activities (Gron et al., 2000; Andreano & Cahill, 2009). Neuroscience research supports such pedagogical alignment, with studies demonstrating distinct memory systems in males versus females (McCarthy et al., 1997; Mather & Lighthall, 2012), indicating that instructional design could leverage these differences (e.g., using imagery mnemonics for one group and story mapping for the other). Educational neuropsychologists have argued that tailoring instruction to cognitive profiles can mitigate gender gaps in subjects like mathematics and reading (Kulturel-Konak, D'Allegro, & Dickinson, 2011). For instance, integrating verbal explainers and social context in STEM lessons could address girls' learning preferences, while adding spatial reasoning tasks might benefit boys (Meyers-Levy & Loken, 2015). Importantly, any educational adaptation must avoid reinforcing stereotypes. Gender differences are often distributions with substantial overlap; individual assessment should guide instruction (Meyers-Levy & Loken, 2015; Schupp et al., 2003). Thus, teacher training should emphasise neurodiversity, using gender trends as general guides rather than rigid rules (Dwivedi et

al., 2021). Future work could empirically test adaptive curricula or AI-based tutors that use real-time neural/behavioural feedback to personalise learning by gender-related tendencies (Malloy & Gonzalez, 2024).

4.2. Behaviour Modelling

Understanding neural decision mechanisms aids the development of computational models of behaviour. Cognitive models (e.g., dual-process or reinforcement learning models) can incorporate sex-specific parameters for risk preference, delay discounting, or memory use (Bechara, Damasio, & Damasio, 2000; O'Doherty et al., 2003). Such models improve predictions of students' or consumers' choices. For example, an AI-driven learning analytics system might model a student's engagement level by integrating physiological proxies (such as pupil dilatation, and EEG features) with gender-informed priors (O'Doherty et al., 2003; Golnar-Nik, Farashi, & Safari, 2019). In simulations of group behaviour, accounting for male/female differences in information weighting could yield more accurate forecasts. In essence, neuroscience provides constraints for the agents in computational models of decision-making. This integration, bridging data-driven AI with theory-driven cognitive modelling, can enhance personalised recommendations in educational apps or decision-support systems (LeCun, Bengio, & Hinton, 2015).

However, rigorous validation and transparency are needed, and models must be tested to ensure they do not encode biases (Buslón et al., 2023).

4.3. Responsible AI and Ethical Considerations

AI's role in decoding brain data raises ethical issues. Biased datasets or assumptions can propagate gender stereotypes. Indeed, recent analyses show that many AI models (in neuromarketing and beyond) are trained predominantly on male-biased data, leading to skewed outcomes (Buslón et al., 2023). For example, algorithms that overestimate female preference for certain colours without cultural nuance a noted bias (Buslón et al., 2023; Stefko et al., 2021). In educational AI, bias could manifest as personalised learning paths that inadvertently favour one gender. To counter this, developers should use diverse, representative training data and include fairness constraints (Dwivedi et al., 2021; Kumar et al., 2015). Regulatory guidelines (e.g., from interdisciplinary AI ethics frameworks) should be applied to neurometric applications, including informed consent for neurodata, privacy protection, and avoiding manipulative uses of gender-based insights (Fisher, Chin, & Klitzman, 2010). Researchers and educators must also practice reflexivity: recognising that brain differences do not deterministically fix abilities or roles (Pessoa, 2008). Neuro-education should empower learners, not pigeonhole them. For example, if an AI tutor identifies a boy's stronger spatial focus, it might adapt by providing spatial visual aids, but it should not assume the boy cannot excel in verbal domains (Meyers-Levy & Loken, 2015). Responsible AI requires continuous monitoring to detect unintended consequences, such as reinforcing societal biases in gender and culture (Chiu & Hong, 2007). Collaboration between neuroscientists, educators, ethicists, and technologists is essential to ensure beneficial outcomes.

In summary, gender-specific neural mechanisms offer valuable insights for cognitive neuroscience and education. By explicitly incorporating these findings, educators can design gender-sensitive pedagogies that respect individual differences, while AI tools can personalise learning ethically. The integrated perspective also calls for behavioural models that combine neurological data with computational theory, opening avenues for adaptive technologies that support diverse learners. Ultimately, this reframed approach aligns with the cognitive and educational orientation of the field, moving beyond commercial neuromarketing to applications in teaching and learning. Further research should empirically test these applications (e.g., intervention studies in classrooms) and refine AI systems with fairness in mind.

5. Conclusions

This review demonstrates that gender shapes neural decision-making via distinct yet overlapping cognitive-affective strategies: women predominantly engage semantic-relational and emotional networks (e.g., medial PFC, amygdala), while men show stronger visuospatial and analytic processing (e.g., occipito-parietal cortex). These differences manifest in memory, attention, and risk-reward tasks, and can be decoded with high precision using AI-enhanced analyses of EEG, fMRI, and fNIRS data. Educationally, these insights support gender-sensitive pedagogies, such as narrative-based learning for girls and spatial-visual for boys, while emphasising individualised assessment to avoid stereotyping. Behaviourally, integrating sex-specific neural parameters into computational models enhances the prediction of learner engagement and decision patterns. Finally, the responsible application of AI requires diverse training data, ethical oversight, and transparency to prevent perpetuating biases. Future work should empirically validate adaptive curricula and AI tutors in real-world settings, ensuring that neuroscientific insights empower rather than pigeonhole learners.

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