JBM
The Journal of Business and Management
(B category academic journal as per UGC Nepal classification)

ISSN 2350-8868
Volume IX | Issue 1 | June 2025

Impact of Cognitive Bias on the Use of Management Information Systems in Nepalese Commercial Banks

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Received: 7 March 2025
Reviewed: 15 May 2025
Accepted: 30 May 2025
Published: 30 June 2025

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Citation:
Adhikari, S. N. (2025). Impact of cognitive bias on the use of management information systems in Nepalese commercial banks. *The Journal of Business and Management, 9*(1), 59-72. https://doi.org/10.3126/jbm.v9iI.81194

Abstract

Background: Management Information Systems (MIS) play a critical role in enhancing decision-making and operational efficiency in the banking sector. However, the effectiveness of these systems is often undermined by cognitive biases that distort how individuals process and respond to system-generated information. In the context of Nepalese commercial banks, where MIS adoption is increasing, the role of cognitive bias remains underexplored and insufficiently addressed in both research and practice.

Objectives: This study aims to investigate the extent to which cognitive biases anchoring bias, overconfidence bias, loss aversion, and confirmation bias impact the use and effectiveness of MIS in Nepalese commercial banks. The goal is to identify how these psychological factors influence user interaction with MIS and their subsequent decisions.

Methods: A quantitative descriptive-correlational research design was used, employing a structured 23 item questionnaire based on validated constructs. A purposive sample of 571 participants, 371 banking customers and 200 employees from Nepalese commercial banks was selected to gather diverse perspectives on MIS usage and cognitive biases. Data analysis involved SPSS 26.0 for descriptive statistics and AMOS 26.0 for confirmatory factor analysis (CFA) and structural equation modeling (SEM) to evaluate model fit and test the hypothesized relationships between cognitive biases and MIS utilization.

Results: The study found that cognitive biases limit the effective use of MIS. Overconfidence, anchoring, loss aversion, and confirmation bias affect user decisions. These biases lead to ignored alerts, trust on early data, fear of change, and resistance to updates.

Conclusion: Cognitive biases are critical impairments to MIS effectiveness in Nepalese commercial banks. Addressing these through targeted training, cognitive debiasing, and user-centric system design is essential to promote rational decision-making and optimize MIS utility.

Keywords: Cognitive biases, decision-making, management information systems, Nepalese commercial banks, user interaction

JEL Classification: G21, M15, D83, C38, O33

Introduction

Management Information Systems (MIS) play a dynamic role in contemporary banking operations by enhancing operational efficiency, improving customer service, and supporting data-driven decision-making. In Nepalese commercial banks, MIS integrates core banking functions such as tracking financial transactions through Core Banking Systems (CBS), producing regulatory compliance reports, monitoring loan performance and credit risk, and enabling strategic decision-making through real-time data dashboards and analytics (Adhikari & Karki, 2020; Bhattarai, 2020). These systems represent the backbone of data-driven banking services, especially in an environment characterized by increasing competition, regulatory scrutiny, and rapid technological change.

Despite these technological advancements and the growing adoption of MIS, the expected improvements in decision quality and operational effectiveness are often compromised by human cognitive limitations. Behavioral factors, particularly cognitive biases, play a significant role in influencing how bank managers and staff interpret, trust, and act upon the information generated by MIS. Cognitive biases are systematic deviations from rational judgment, including phenomena such as anchoring bias, overconfidence, confirmation bias, and loss aversion (Simon & Groves, 2021; Tversky & Kahneman, 2019). These biases can cause users to misinterpret data, discount warnings, or selectively attend to information that confirms pre-existing beliefs, thereby diminishing the value and reliability of MIS outputs. For instance, an anchoring bias may cause decision-makers to extremely depend on the first set of information received, ignoring subsequent updates and warnings from MIS, while overconfidence may lead to the dismissal of risk indicators generated by the system.

To better understand these behavioral effects, this study adopts Prospect Theory as its theoretical foundation (Kahneman & Tversky, 1979). Prospect Theory explains how individuals evaluate potential gains and losses in decision-making under uncertainty, often departing from purely rational models by presenting loss aversion and framing effects. These behavioral tendencies are particularly relevant in banking, where decisions frequently involve uncertain outcomes and risk assessments based on MIS data. By framing cognitive biases through Prospect Theory, the study aims to disclose how these psychological patterns influence the use and effectiveness of MIS in Nepalese commercial banks.

In the specific context of Nepal's banking sector, cognitive biases may clear in various ways, such as an excessive trust on historical loan performance data (anchoring bias), reluctance to respond to early risk signals flagged by MIS (overconfidence), or hesitancy to take necessary risks suggested by system analysis due to fear of losses (loss aversion). Such tendencies undermine the decision-support role of MIS and can lead to inefficiencies in critical banking functions, including risk management, regulatory compliance, and strategic planning (Chaudhary et al., 2020; Ghimire et al., 2021; Sharma & Shrestha, 2020). Despite the critical importance of these issues, existing research in Nepal has largely focused on technological and organizational factors influencing MIS adoption, with the behavioral dimension especially cognitive biases remaining underexplored.

This study attempts to fill this research gap by investigating how specific cognitive biases affect the effective utilization of MIS in Nepalese commercial banks. The objective is to comprehensively assess the influence of anchoring bias, overconfidence, confirmation bias, and loss aversion on managerial interactions with MIS-generated data and recommendations. By integrating concepts from behavioral economics with information systems research, the study intends to provide actionable insights that can guide the design of MIS interfaces, training programs, and managerial practices aimed at minimizing the adverse impacts of these biases. Ultimately, such efforts can enhance decision quality, improve risk management, and promote more effective and sustainable banking operations.

To achieve these aims, a quantitative research approach employing a structured questionnaire will be utilized, targeting managerial and technical staff in Nepalese commercial banks who regularly use MIS for decision-making. The questionnaire will explore demographic variables, the extent of MIS use, and agreement with statements reflecting the presence of cognitive biases. The collected data has been analyzed using statistical methods to identify significant relationships between biases and MIS utilization patterns, thereby clarifying behavioral barriers to optimal system use.

The findings of this research are anticipated to contribute both theoretically and practically. Theoretically, the study extends the application of Prospect Theory into the domain of information systems within the banking sector in Nepal, highlighting the relevance of cognitive biases in technological adoption and use. Practically, the insights gained will aid banks in implementing bias-aware MIS designs and developing training and governance frameworks that promote rational decision-making. By mitigating the distortive effects of cognitive biases, banks can enhance the reliability of MIS outputs, reduce operational risks, and adapt to a culture of data-driven management. This approach aligns with global best practices emphasizing the integration of human factors in technology utilization to achieve sustainable organizational performance.

Understanding the influence of cognitive biases on the use of Management Information Systems in Nepalese commercial banks is essential for bridging the gap between technological capabilities and actual organizational performance. Addressing these behavioral challenges enables banks to optimize the value of MIS investments, enhance decision-making accuracy, and improve their ability to manage risks and fulfill regulatory demands. As the banking environment becomes increasingly dynamic and data-driven, aligning human behavior with technological systems is energetic for achieving strategic agility, operational efficiency, and long-term sustainability.

Review of Literature

Management Information Systems in Banking

MIS serves a strategic role in modern banking institutions by supporting decision-making, risk management, regulatory compliance, customer relationship management, and strategic planning (Laudon & Laudon, 2020; O'Brien & Marakas, 2011). These systems enable real-time data processing and monitoring, enhancing operational agility and competitive advantage in an increasingly digital environment (Gupta & Kohli, 2006). In Nepalese commercial banks, MIS has become essential to handle complex financial operations, improve service delivery, and fulfill evolving regulations (Adhikari et al., 2022). However, the efficacy of MIS depends not only on its technical capabilities but also on the behavioral responses of users interpreting the system's output.

Cognitive Biases and Decision-Making

Cognitive biases represent systematic deviations from rational judgment and decision-making (Tversky & Kahneman, 1974). These biases are particularly relevant in financial decision contexts characterized by uncertainty and risk (Barberis & Thaler, 2003; Kahneman & Tversky, 1979). Prospect Theory, proposed by Kahneman and Tversky (1979), explains how individuals evaluate potential gains and losses asymmetrically, often placing greater weight on avoiding losses than acquiring gains. Such biases can undermine the objectivity of decisions based on MIS data. Recent studies emphasize the importance of incorporating behavioral insights into information systems design to improve technology adoption and utilization (Bhattacherjee, 2001; Gefen et al., 2003).

Anchoring and Overconfidence Bias

Anchoring bias occurs when decision-makers excessively rely on initial information or reference points when making subsequent judgments (Tversky & Kahneman, 1974). Within MIS use, this bias may cause managers to cling to outdated performance data or early risk assessments despite updated system reports suggesting otherwise (Sharma & Shrestha, 2020). Overconfidence bias, defined as an inflated belief in one's own knowledge or predictive ability, often leads managers to discount MIS recommendations and depend heavily on intuition (Klayman et al., 1999; Moore & Healy, 2008). Research shows that overconfidence is prevalent among experienced professionals and can result in forecasting errors and risk mismanagement (Dhungana et al., 2022; Hilary & Menzly, 2006).

Loss Aversion and Confirmation Bias

Loss aversion refers to the tendency to prefer avoiding losses over acquiring equivalent gains (Kahneman & Tversky, 1979). In banking, this bias may cause decision-makers to hesitate acting on MIS risk alerts due to fear of reputational or financial damage, even when early intervention is warranted (Tversky & Kahneman, 1991). Confirmation bias leads users to favor information that confirms existing beliefs while disregarding contradictory MIS data (Nickerson, 1998; Oswald & Grosjean, 2004). This bias can cause defective assumptions within organizational cultures and reduce the effectiveness of MIS outputs.

Empirical Gaps in MIS and Cognitive Bias Research

Despite strong theoretical foundations, empirical studies investigating the impact of cognitive biases on MIS utilization in developing countries, including Nepal, remain limited. While international literature addresses behavioral factors in technology adoption and decision support (Arnott, 2006; Davis, 1989; Venkatesh et al., 2003), Nepalese studies largely focus on infrastructure, user training, and organizational readiness (Adhikari et al., 2022; Gautam et al., 2023). The behavioral dimensions of MIS use, particularly how cognitive biases influence decision-making in banking operations like loan approvals and risk management, are underexplored, enlightening a significant knowledge gap.

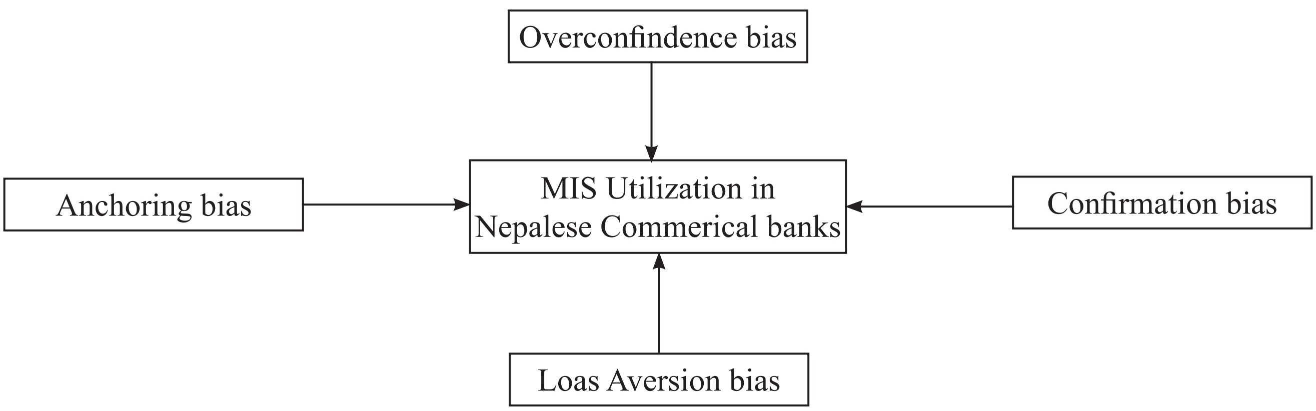
Theoretical Framework: Prospect Theory and MIS Use

The current study draws on Prospect Theory to develop a conceptual framework linking cognitive biases and MIS utilization. This framework suggests that while MIS delivers objective, data-driven recommendations, cognitive biases moderate user responses. Anchoring bias may inhibit adjustment to new information; overconfidence may lower trust in MIS outputs; loss aversion may delay critical risk responses; and confirmation bias may distort data interpretation (Chen, Xu, & Zhang, 2022; Kahneman & Tversky, 1979; Karmacharya et al., 2022). Such a behavioral-technology interaction model helps to explain challenges in achieving effective MIS-supported decision-making in financial institutions (Sarmah et al., 2021).

Conceptual Framework

Figure 1

Conceptual framework developed by the researcher based on prospect theory



Hypothesis

H0: Cognitive biases negatively influence the effective use of MIS in decision-making processes within Nepalese commercial banks.

Some specific hypotheses are derived from the overall hypothesis to examine how individual cognitive biases influence the effective use of Management Information Systems (MIS) in Nepalese commercial banks. These specific hypotheses target distinct behavioral tendencies that may interfere with data-driven decision-making processes.

H01: Anchoring bias negatively affects the effective utilization of MIS in Nepalese commercial banks.

H02: Overconfidence bias reduces reliance on MIS outputs among managers in Nepalese commercial banks.

H03: Loss aversion bias negatively impacts timely and optimal risk-based decision-making, even when MIS provide accurate recommendations in Nepalese commercial banks.

H04: Confirmation bias distorts the interpretation of MIS information, reinforcing pre-existing beliefs in Nepalese commercial banks.

Research Design

Study Design

This quantitative research employed a cross-sectional survey to investigate the impact of cognitive biases on the use of MIS in Nepalese commercial banks. Using a causal-comparative approach, the study focused on biases such as anchoring, overconfidence, loss aversion, and confirmation bias. Structural Equation Modeling (SEM) was applied to analyze the relationships among these variables (Creswell, 2014; Hair et al., 2010).

Population and Sample

The population targeted two primary groups: commercial bank customers actively using electronic banking services and bank employees including branch managers, IT staff, and operational personnel, given their direct interaction with MIS. This dual sampling enables capturing both user and provider perspectives on MIS usage. The total sample comprised 571 participants among them 371 customers and 200 employees, which satisfies the recommended minimum sample size for SEM analyses, generally suggested as at least 200 cases or a ratio of 10 respondents per estimated parameter (Hair et al., 2010; Kline, 2015).

Sampling Technique

Convenience sampling, a non-probability technique, was used due to resource constraints and accessibility considerations. This method is widely employed in behavioral and MIS research where randomized sampling is difficult, and it allows rapid data collection from available respondents (Etikan et al., 2016). Although convenience sampling limits generalizability, its pragmatic use is justified given the exploratory nature of this study and focus on readily accessible participants.

Data Collection Procedure and Ethical Considerations

Data were collected using self-administered questionnaires distributed both physically and electronically from January to March 2025. The survey captured cognitive bias and MIS usage data through standardized items. Ethical protocols were strictly followed: participants received full explanations of the study purpose, voluntary participation was emphasized, informed consent was obtained, and confidentiality ensured by omitting personal identifiers. Ethical clearance was granted by the affiliated academic institution, aligning with standard research ethics guidelines (Resnik, 2018).

Measures

The instrument consisted of 18 Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) adapted from validated scales in behavioral economics and MIS research. The constructs measured were anchoring bias (4 items), overconfidence bias (3 items), loss aversion (3 items), confirmation bias (3 items), and use of MIS (5 items). These items were coded as AB1–AB4, OB1–OB3, LB1–LB3, CB1–CB3, and UMI1–UMI5, respectively. Adapting established scales ensures content validity and comparability with prior research (Podsakoff et al., 2003).

Instrument Validity and Reliability

A pilot test with 30 participants assessed instrument reliability and clarity. Cronbach's Alpha values for all constructs exceeded 0.70, indicating good internal consistency (Nunnally & Bernstein, 1994). Confirmatory Factor Analysis (CFA) was performed to verify construct validity, confirming that items loaded appropriately onto their respective latent variables. Revisions were made based on expert feedback from academics and banking professionals to enhance clarity and contextual relevance.

Data Analysis Techniques

Data analysis was conducted using SPSS version 26.0 and AMOS version 26.0. Descriptive statistics (frequencies, means, and standard deviations) summarized respondent characteristics and general trends. SEM tested the hypothesized relationships, enabling simultaneous analysis of direct and indirect effects among latent variables. Model fit was evaluated using standard indices including the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Goodness-of-Fit Index (GFI), following accepted SEM reporting standards (Hu & Bentler, 1999).

Results and Discussion

Demographic Data Analysis

Table 1 shows that 57.2% of respondents were male, and 42.8% were female. The largest age group was 25–35 years (45.4%), followed by 35–50 years (36.4%). Most respondents (66.0%) reported using MIS daily, while 31.7% used it weekly, and 2.3% monthly.

Regarding banking experience, 55.4% had 2–5 years of experience, indicating a relatively young and experienced workforce. Additionally, 57.8% reported operational-level ICT knowledge, while only 0.3% had minimal exposure, suggesting that most respondents were sufficiently skilled to use MIS effectively.

Table 1

Socio-demographic characteristics of respondents (N = 571)

	Characteristics	N	%
Gender			
	Male	327	57.2
	Female	244	72.8
Age			
	Below 25 Years	47	8.2
	25-35 years	259	45.4
	35-50 years	208	36.4
	More than 50 years	57	10.0

Frequency of MIS Uses		
Daily	377	66.0
Weekly	181	31.69
Monthly	13	2.31
Banking Experience		
Below 2 years	53	9.2
2-5 years	316	55.4
5-8 years	171	30.4
More than 8 years	29	5.0
ICT Knowledge		
Few	2	0.3
Basic	122	21.4
Operational	330	57.8
High	117	20.5

Note. Based on field survey conducted by the researcher (January–March 2025).

An 18-item five-point Likert scale (1 = strongly agree to 5 = strongly disagree) was used to assess cognitive biases and the use of MIS. Table 2 describes the mean values for all items which were below 3.0, suggesting a general agreement among respondents with the presented statements (Awang, 2012). According to Norman (2010), Likert-scale means below the midpoint indicates agreement and supports the interpretation of behavioral tendencies. Furthermore, the cognitive bias constructs anchoring, overconfidence, confirmation bias, and loss aversion used in this study are grounded in well-established behavioral theory (Kahneman, 2011), reinforcing their relevance in evaluating MIS usage behavior.

Table 2

Factors affecting the use of MIS

Items	Mean	Std. Deviation
Anchoring Bias		
AB1. People trust too much on the first information they receive.	1.981	0.627
AB2. Even when MIS provides better data, they hesitate to change	1.635	0.712
AB3. Avoids new technology or methods.	1.572	0.688
AB4. They trust old ways instead of updating their thinking based on new reports.	2.081	0.612
Overconfidence Bias		
OB1. People believe their own judgment is better than what MIS suggests.	1.567	0.732
OB2. They ignore warnings or reports from MIS, thinking they don’t need them	1.782	0.691
OB3. They prefer making decisions based on experience rather than data.	1.810	0.701
Loss Aversion		
LB1. People avoid new MIS features because they fear losing control.	2.211	0.813
LB2. Even when MIS shows a better way, they stick to familiar methods.	1.891	0.802
LB3. They feel safer with manual processes rather than trusting digital tools.	1.991	0.765
Confirmation Bias		

CB1. People focus only on MIS reports that support what they already believe.	2.001	0.821
CB2. They ignore or avoid data that challenges their views.	2.121	0.792
CB3. Instead of using MIS to explore all options, they pick only what fits their thinking.	1.78	0.871
Use of MIS		
UMI1. MIS gathers relevant data from various sources for informed decision-making.	1.881	0.761
UMI2. MIS centralizes data storage, ensuring easy access and consistency across departments.	1.781	0.771
UMI3. It provides real-time updates, enabling quick actions based on current information.	1.710	0.841
UMI4. MIS supports decision-making by offering insights and analysis to managers.	1.563	0.734
UMI5. It automates routine tasks, improving efficiency and reducing errors.	1.991	0.804
N=571, 1=Strongly Agree, 2= Agree, 3=Neutral, 4= Disagree, 5= Strongly Disagree		

Note. Field survey by researcher (Jan–Mar 2025) and SPSS analysis.

Confirmatory Factor Analysis (CFA)

CFA is a method within SEM and factor analysis that assesses whether observed variables align with latent or unobserved variables. This study aims to determine how factors such as anchoring bias, loss aversion bias, overconfidence bias and confirmation bias influence the use of management information system.

To achieve this, the research surveyed 571 individuals from various banks. The questionnaire covered all relevant factors. Factor analysis, used to reduce a large number of variables into a manageable set of factors, was employed in this study. Prior to conducting CFA, prerequisites such as multivariate normality, multicollinearity, and sample size were carefully examined.

Reliability and Validity Analysis

In principle, reliability and validity are interconnected concepts. The construct validity of all constructs was assessed using Confirmatory Factor Analysis (CFA). Construct validity comprises two key types of validity - discriminant validity ensures constructs are distinct, while convergent validity confirms they accurately measure what they are intended to.

Table 3

Reliability and convergent validity

Items	Alpha	Composite Reliability	AVE
Anchoring Bias	.925	.833	.625
Loss Aversion	.959	.956	.887
Overconfidence Bias	.935	.929	.815
Confirmation Bias	.828	.937	.834
Use of MIS	.831	.956	.876

Average Variance Extracted (AVE): AVE measures convergent validity, reflecting how well a construct shares its items or statements. For all variables, the AVE values exceed 0.5: Anchoring Bias = 0.625, Loss Aversion = 0.887, Overconfidence Bias = 0.815, Confirmation Bias = 0.834 and Use of MIS =

0.876. This indicates that the model demonstrates convergent validity.

Composite Reliability (CR): CR evaluates the significance of items by examining factor loadings. The CR values for all constructs are above 0.7: Anchoring Bias = 0.833, Loss Aversion = 0.956, Overconfidence Bias = 0.929, Confirmation Bias = 0.937 and Use of MIS = 0.956. This confirms the composite reliability of the model.

Internal Consistency: Internal consistency assesses how well a factor is related to other factors, typically measured using Cronbach's alpha. All variables have Cronbach's alpha values exceeding 0.7: Anchoring Bias = 0.925, Loss Aversion = 0.959, Overconfident Bias = 0.935, Confirmation Bias = 0.828 and use of MIS = 0.831. This indicates strong internal consistency within the model.

Discriminant validity in the study was evaluated using two methods: the Fornell and Larcker Criterion and the Heterotrait-Monotrait (HTMT) Ratio. According to the Fornell and Larcker Criterion, discriminant validity is confirmed if the square root of the Average Variance Extracted (AVE) for a construct is greater than its correlation with other constructs. However, this criterion has faced criticism, and the HTMT Ratio has become a more widely accepted method for assessing discriminant validity. In this study, discriminant validity was not fully established using the Fornell and Larcker Criterion. Nevertheless, the HTMT Ratio analysis showed that all ratios were below the recommended threshold of 0.85 (Henseler et al., 2015), indicating that discriminant validity was achieved. The results of the discriminant validity assessment are summarized in Table 4.

Table 4

HTMT analysis

	F4	F5	F9	F10
F4				
F5	0.427			
F9	0.478	0.464		
F10	0.426	0.404	0.674	

Thus, with all the reliability and validity criteria met, the confirmatory factor analysis model is deemed effective for evaluating the contribution of the factors in assessing the impact of cognitive bias on the use of MIS.

CFA Model Fit

The fit statistics referring to this measurement model showed adequate fit represented by values of 0.9 or above for NFI, TLI, CFI and less than 0.8 for RMSEA (Bagozzi &Yi, 1998). The chi- square of this model was 315.492, at DF of 119 (p=0.00), also indicative of data fit. Chi-square / degrees of freedom are represented by the value 2.91, which is less than 5.0. Other less favorable indicators were GFI=.915 and AGFI= .902, which were greater than 0.9. Therefore, the goodness of fit statistics illustrated that the structural model fitted well with the data.

Significance testing Using SEM

The structural model represents the second stage and final step in the SEM approach. This model integrates and correlates all the factors with the use of MIS constructs. It establishes a structural link between the cognitive bias and the use of MIS. The fit statistics referring to this measurement model showed adequate fit represented by values of 0.9 or above for NFI, TLI, CFI and less than 0.8 for RMSEA (Bagozzi &Yi, 1998). The chi- square of this model was 314.569, at DF of 119 (p=0.00), also indicative of data fit. Chi-square / degrees of freedom are represented by the value of 2.643, which is less than 5.0. Other less favorable indicators were GFI=.981 and AGFI= .975, which were greater than 0.9. Therefore, the goodness of fit statistics illustrated that the structural model fitted well with the data.

Hypothesis Testing

SEM using AMOS was employed to test the hypothesized relationships between cognitive biases and the use of MIS in Nepalese commercial banks. Table 6 presents the standardized path coefficients, standard errors (S.E.), critical ratios (C.R.), and p-values for each relationship.

Table 5

Path coefficients from SEM analysis

Variable			Estimate	S.E.	C.R.	P	Remarks
Use of MIS	<---	Anchoring Bias	.270	.042	4.538	***	Significance
Use of MIS	<---	Overconfidence Bias	.206	.027	5.469	***	Significance
Use of MIS	<---	Loss Aversion	.115	.039	2.092	.036	Significance
Use of MIS	<---	Confirmation Bias	0.231	.049	3.142	0.012	Significance

All four cognitive biases demonstrated statistically significant effects on MIS use. The p-values for each relationship were below the 0.05 significance threshold, indicating the rejection of the null hypotheses (H1–H4). Furthermore, the critical ratios (z-scores) for each bias exceeded the threshold value of 1.96, supporting the statistical significance of these effects.

This study explored the impact of four cognitive biases—anchoring bias, overconfidence bias, loss aversion, and confirmation bias—on the use of Management Information Systems (MIS) within Nepalese commercial banks. Using Structural Equation Modeling (SEM), the findings reveal that each of these biases significantly affect MIS usage, highlighting the role of human cognition in shaping digital decision-making practices.

Anchoring bias showed the strongest positive effect on MIS use ($\beta = 0.270$, $p < 0.001$), indicating that users often rely heavily on initial information, such as default MIS inputs or historical data, even when more relevant or recent data is available. This behavior supports earlier cognitive theories (Tversky & Kahneman, 1974) and justifies the need to address rigid decision anchors within MIS environments.

Confirmation bias was also influential ($\beta = 0.231$, $p = 0.012$), suggesting users interpret information selectively to confirm their pre-existing beliefs. This bias can hinder objective analysis, particularly in data-rich environments like MIS, and supports Nickerson's (1998) claim that people often seek cognitive consistency at the expense of accuracy.

Overconfidence bias ($\beta = 0.206$, $p < 0.001$) reveals that users may overly trust their interpretations of MIS data, ignoring limitations or contrary evidence. This behavior aligns with Moore and Healy's (2008) findings, reinforcing the importance of improving users' self-awareness and critical thinking in MIS settings.

Although weaker in magnitude, loss aversion ($\beta = 0.115$, $p = 0.036$) was statistically significant, indicating that risk-averse users may avoid certain MIS features to prevent perceived losses. This reflects the foundational work of Kahneman and Tversky (1979) and suggests that loss-sensitive users might underutilize analytical tools that could otherwise benefit decision-making.

Conclusion and Suggestions

This study confirms that cognitive biases significantly impact the use of MIS in Nepalese commercial banks. Decision-makers are influenced by psychological tendencies rather than purely rational thinking when engaging with MIS. Among the biases examined, anchoring and confirmation biases have the strongest effects, followed by overconfidence and loss aversion. These biases constrain the effective use of MIS, leading to best decisions and underutilization of technological capabilities. Therefore, MIS effectiveness depends not only on technical factors but also on recognizing and addressing users' cognitive limitations. Integrating behavioral awareness into MIS implementation and user training is essential to enhance the value derived from MIS investments.

To mitigate these challenges, organizations should incorporate behavioral science modules in MIS training programs to increase awareness of cognitive biases and encourage rational decision-making. MIS interfaces should be designed to minimize anchoring and confirmation biases by providing balanced information, highlighting updates, and encouraging different viewpoints. Organizations must adopt a culture that promotes critical evaluation of MIS outputs through questioning assumptions, validating data, and consulting multiple sources to reduce overconfidence. Establishing familiar environments will allow users to safely explore MIS features, reducing loss aversion and increasing familiarity with system capabilities. Moreover, banking regulators and policymakers should formulate guidelines that integrate behavioral insights to improve system governance and user accountability. Further research linking cognitive psychology and MIS in emerging economies is important to improve how these systems are designed, adopted, and used.

Author contribution statement

The author solely conducted conceptualization, data collection, analysis, writing tasks, addressing the comments of reviewers, and finalizing the manuscript.

Funding

There is no funding support for this study.

Declaration statement

The authors declare no conflict of interest.

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