Impact of Occupation of Banking Customers on Artificial Intelligence-driven Financial Assistant Adoption Factors and Behavioural Intention to use AIFA

Ms. Nisha Rani
Research Scholar, Haryana School of Business,
Guru Jambheshwar University of Science & Technology
Hisar, Haryana
Email:nisha.garg1987@gmail.com

Dr. Tilak Sethi
Professor (Retired), Haryana School of Business, Guru Jambheshwar University of Science & Technology
Hisar, Haryana
*Email:*tilaksethi@hotmail.com

Dr. Pardeep Gupta
Professor, Haryana School of Business, Guru Jambheshwar University of Science & Technology
Hisar, Haryana
*Email:*pardeephsb@gmail.com

Abstract— Artificial Intelligence-driven financial assistants provide an accessible, responsive and 24/7 service offering insights into spending habits, suggesting savings plans and even resolving queries related to banking tasks. The adoption of AI-powered financial assistants in the banking sector is revolutionizing how financial services are delivered, offering a combination of convenience, personalized services, and improved operational performance. The usage of the Artificial Intelligence-driven Financial Assistant services in the banking sector is the latest wave of new technologies adopted. As more customers are inclining towards tech-based services, the aim of the present study is to examine the impact of demographic variable i.e occupation on the Customer's adoption factors of AI-driven financial assistant. The study is based on primary data collected through an adapted questionnaire that contains the six major adoption factors of AI-driven financial assistants such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Personal Innovativeness, Trust and Behavioural Intention to use AI-driven financial assistant. The data has been collected from 374 banking customers of Haryana through a survey. ANOVA has been used to identify the findings and the result of the present study indicates that based on occupation, significant difference found in customer's adoption factors of Personal Innovativeness while no significant difference found in Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Trust. In addition to this, behavioural intention to use AIFA also differentiate among different groups based on occupation. AI-driven financial assistant services are transforming the way banks interact with customers and streamline internal processes. The results of the present study will help banks and financial institutions to better understand their customers.

Keywords: Artificial Intelligence (AI), Banks, AI-driven financial assistant, Customers adoption factors, Behavioral Intention to use AIFA.

I. INTRODUCTION

The usage of Artificial Intelligence (AI)-driven Financial Assistant services in the banking sector represents a significant technological advancement that is transforming the industry (Patil & Kulkarni, 2019). These AI-powered tools are designed to help financial institutions streamline operations, enhance customer service, and offer personalized banking experiences (Bhattacharya & Sinha, 2022). By leveraging machine learning algorithms, natural language processing, and data analytics, these AI assistants can efficiently handle tasks such as answering customer queries, providing financial advice, processing transactions, and offering tailored product recommendations (R. & Ravi, 2021).

AI-driven financial assistants can analyze vast amounts of financial data in real-time, enabling them to make more accurate predictions and assist in decision-making (Vijai, 2018). This technology not only improves operational efficiency but also reduces human errors and the need for

ISBN: 978-93-343-1044-3

manual intervention. For customers, AI assistants provide an accessible, responsive, and 24/7 service, offering insights into spending habits, suggesting savings plans, and even helping manage investments (Richad et al., 2019).

Moreover, AI can enhance the security of financial transactions by detecting unusual activities and potential fraud, making banking services safer for customers (Soni, 2019; Venkatesan & Sumathi, 2019). As the banking sector continues to evolve, the integration of AI-driven financial assistants is expected to further transform how banks operate, improving both customer satisfaction and the efficiency of banking services. The adoption of AI-powered financial assistants in the banking sector is revolutionizing how financial services are delivered, offering a combination of convenience, personalized services, and improved operational performance (Patil & Kulkarni, 2019). For banks and financial institutions, the integration of AI can streamline internal processes and enhance operational efficiency. AI can automate routine tasks such as processing transactions, managing customer service inquiries, and identifying fraud patterns, freeing up staff to focus on more complex issues. Additionally, AI can improve decision-making by analyzing vast amounts of customer data, uncovering insights into individual financial behaviour, preferences, and needs. This data can then be used to offer more personalized services and products, improve customer satisfaction, and even anticipate customer needs before they arise.

II. OBJECTIVES OF THE STUDY

- To examine the impact of occupation on the Customer's adoption factors of AI-driven financial assistant.
- To examine the impact of occupation on the Behavioural Intention to use AI-driven financial assistant.

III. LITERATURE REVIEW

- Performance expectations, effort expectations and perceived credibility have significant effects on consumers' behavioural intentions regarding innovative banking products as consumers give importance to elements such as time, performance, ease of use, security and safety (Gundes & Sazkaya, 2018).
- The economic value, technical know-how, security, privacy have positive effect on adoption behaviour of digital payment system (Mishra & Ghumre, 2020).
- AI quality is positively associated with satisfaction and satisfaction is positively associated with the intention to continue using e-banking services in Nigeria (Dantsoho et al. ,2021).
- Various factors such as perceived risk, perceived privacy, enjoyment, social influence, and perceived strength of control contribute towards chatbot advisor adoption intentions in financial services due to the convenience and time savings. (Patil & Kulkarni, 2019).
- Innovativeness, perceived usefulness, perceived ease of use and attitude towards using the chatbot affected behavioural intention as the chatbot technology helps in financial transactions with a bank due to its usefulness and the ease of use (Richad et al., 2019).
- Information, entertainment, media appeal and social presence positively predicted user satisfaction, while perceived privacy risks reduced satisfaction and user satisfaction had a positive impact on both continued use of chatbot services and customer loyalty (Cheng & Jiang,2020).
- Information quality, service quality and system quality have an impact on customer experience (Trivedi, 2019).

IV. RESEARCH METHODOLOGY

- The study is based on primary data collected through a questionnaire that contains the six major adoption factors of AI-driven financial assistants such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Personal Innovativeness and Trust to use AI-driven financial assistant along with dependent variable as Behavioural Intention to use AI-driven financial assistants.
- The data has been collected from 374 banking customers of Haryana through a survey.

ISBN: 978-93-343-1044-3

- Secondary Data has been gathered from magazines, books, journals, and websites to complement the primary data.
- Statistical tools such as ANOVA has been used to analyse the customer adoption factors of AI driven financial assistant and the impact of demographic variable i.e. occupation on these adoption factors and Behavioural Intention to use AI-driven financial assistants.
- The Levene's Test statistics has been used to check the assumption of homogeneity of variances and accordingly F statistics and Welch test has been used to identify the significant difference among the groups of different adoption factors.
- To know the exact differences among the groups, Post Hoc test with Tukey method has been applied when the assumption of homogeneity of variances is not violated and Games Howell method has been applied when the assumption of homogeneity of variances is violated.

V. HYPOTHESIS OF THE STUDY

H1: There is significant difference between the Performance Expectancy of AIFA on the basis of Occupation of the respondents.
H2: There is significant difference between the Effort Expectancy of AIFA on the basis of Occupation of the respondents.
H3: There is significant difference between the Social Influence of AIFA on the basis of Occupation of the respondents.
H4: There is significant difference between the Facilitating Conditions of AIFA on the basis of Occupation of the respondents.
H5: There is significant difference between the Trust of AIFA on the basis of Occupation of the respondents.
H6: There is significant difference between the Personal Innovativeness of AIFA on the basis of Occupation of the respondents.
H7: There is significant difference between the Behavioural Intention to use AIFA on the basis of Occupation of the respondents.

VI. RESULTS AND DISCUSSION

A. Demographic Profile of Respondents

This section contains the findings and interpretation of the survey conducted regarding customer adoption factors and Behavioral Intention to use AI-driven Financial Assistant as follows:

Table 1: Demographic Attributes of Respondents

	Categories	Frequency	Percentage	Cumulative Percentage
Gender	Male	219	58.6	58.6
	Female	155	41.4	100
	Total	**374**	**100**	
The bank you deal with	Public Sector Bank	230	61.5	61.5
	Private Sector Bank	144	38.5	100
	Total	**374**	**100**	
Occupation	Student	67	17.9	17.9
	Private Employee	76	20.3	38.2
	Govt. Employee	169	45.2	83.4
	Self-Employed	38	10.2	93.6
	Professional	24	6.4	100.0
	Total	**374**	**100**	

Source: Field Survey Data

The above Table 1 explains the findings of the frequency and percentage analysis of demographic attributes of 374 respondents who responded to the study. The demographic attributes are Gender, The Bank You Deal With, Age, Average Monthly Income who responds. Table 1 shows that the majority proportion of the respondents are male (58.6%) as compared to the proportion of females (41.4%). According to the survey results, the majority of the respondents are dealing with Public Sector Bank (61.5%) followed by Private Sector Bank (38.5%).

The result of the study also found that a large percentage of customers belongs to the occupation of group of Govt employees (45.2%) followed by the group of private employee (20.3%) , group of student (17.9%) and self-employed (10.2 %) and professional (6.4%).

ISBN: 978-93-343-1044-3

B. Reliability and validity of the Instrument and Pilot testing

The validity and reliability of the questionnaire were examined prior to analysis of the survey data.

Table 2: Reliability Statistics

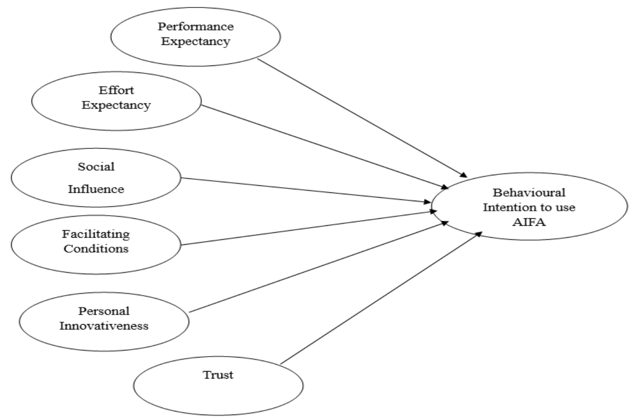
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.968	.968	39

The reliability of this questionnaire is examined by using Cronbach's alpha with the help of SPSS software. Generally, a Cronbach's alpha of more than or equal to 0.70 is considered as Good for the reliability of the questionnaire. According to the study, the questionnaire's Cronbach's alpha is 0.968 as per table 2, which is higher than 0.7 for the 39 items and indicates that reliability has been achieved. Overall, these results suggest that the scale is well-designed, with a strong internal consistency that supports its reliability in measuring the intended construct.

The validity of the questionnaire was measured by the discussion and interviews with the panel of experts in the area of banking and finance and also with the experts in the questionnaire making for the better understanding of language and scales used. After preparation of the questionnaire, pilot study was carried out. As per the suggestion made by the sample respondents, questionnaire was revised and few questions were added and deducted. The preliminary results were taken to check the normality, reliability and validity of the survey instrument. The questionnaire was developed after a thorough examination of the literature. Additionally, the questionnaire is tailored based on expert recommendations. As a result, the created questionnaire was suitable for the current study.

C. THE CONCEPTUAL MODEL

The conceptual model used is the present study as depicted in the below diagram is having six independent variables as customer adoption factors of AIFA with one dependent variable as Behavioral Intention to use AIFA based on UTAUT-2 model with some additional construct as independent variables based on the area specific of the present study i.e. banking with the use of technology.



Source: Designed by the Author based on Literature Review

D. Comparison of the customer adoption factors and Behavioural Intention to use AIFA on the basis of occupation

Table 3: Analysis of variance across the occupation of banking customers

Customer Adoption Factors	Levene Statistic	Sig.	F value	Sig.	Welch	Sig.	Hypothesis (Accepted/ Rejected)
Performance Expectancy	3.698	.006	NA		1.132	0.346	Rejected
Effort Expectancy	2.587	.037	NA		1.953	0.108	Rejected
Social Influence	2.501	.042	NA		1.012	0.405	Rejected
Facilitating Conditions	4.109	.003	NA		1.774	0.140	Rejected
Trust	1.314	.264	1.081	.366	NA		Rejected
Personal Innovativeness	4.798	.001	NA		4.200	0.004	Accepted
Behavioural Intention to use AIFA	1.055	.379	3.926	.004	NA		Accepted

The results of the table 3 shows that the Levene's Test statistics for adoption factors as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Personal

ISBN: 978-93-343-1044-3

Innovativeness are found significant which means the assumption of homogeneity of variances is violated, so Welch test results has been considered to identify the significant difference among the groups across occupation.

The Levene's Test statistics for adoption factor Trust found insignificant which means the assumption of homogeneity of variances is not violated, so Anova F Statistics results are considered to find out the significant difference among the groups across occupation. Similarly, the Behavioural Intention to use AIFA also found insignificant which means the assumption of homogeneity of variances is not violated, so Anova F Statistics results are considered to find out the significant difference among the groups across occupation.

The result of the Welch test shows that there is no significant difference for the factor Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions among the different groups on the basis of occupation, hence H1, H2, H3, H4 are rejected. The result of the Welch test shows that there is significant difference for the factor Personal Innovativeness among the different groups on the basis of occupation, hence H6 is accepted and further Post-Hoc Analysis among different groups has been done with Games Howell Method.

The result of the Anova F Statistics shows that there is no significant difference for the factor Trust among the different groups on the basis of occupation, hence H5 is rejected. The result of the Anova F Statistics shows that there is significant difference for the factor Behavioural Intention to use AIFA among the different groups on the basis of occupation, hence H7 is accepted and further Post-Hoc Analysis among different groups has been done with Tukey HSD Games Howell Method.

Table 4: Multiple Comparisons with Games Howell Method for Personal Innovativeness across Occupation

(I)Occupation	(J) Occupation	Mean Difference (I-J)	Std. Error	Sig.
Student	Private Employee	-.38071	.15708	.116
	Govt. Employee	-.44924*	.14147	.017
	Self-Employed	-.03598	.21425	1.000
	Professional	-.02326	.21573	1.000
Private Employee	Student	.38071	.15708	.116
	Govt. Employee	-.06853	.10706	.968
	Self-Employed	.34474	.19327	.393
	Professional	.35746	.19490	.370
Govt. Employee	Student	.44924*	.14147	.017
	Private Employee	.06853	.10706	.968
	Self-Employed	.41327	.18081	.168
	Professional	.42599	.18255	.164
Self-Employed	Student	.03598	.21425	1.000
	Private Employee	-.34474	.19327	.393
	Govt. Employee	-.41327	.18081	.168
	Professional	.01272	.24334	1.000
Professional	Student	.02326	.21573	1.000
	Private Employee	-.35746	.19490	.370
	Govt. Employee	-.42599	.18255	.164
	Self-Employed	-.01272	.24334	1.000

* The mean difference is significant at the 0.05 level.

The results of the table 4 shows that for the adoption factor Personal Innovativeness, student group significantly differ particularly with the Govt employee group. However, there are no significant differences when comparing other groups on the basis of occupation.

Table 5: Multiple Comparisons with Games-Howell Method for Behavioural Intention to use AIFA across Occupation

(I)Occupation	(J) Occupation	Mean Difference (I-J)	Std. Error	Sig.
Student	Private Employee	-.41289*	.14765	.043
	Govt. Employee	-.44106*	.12720	.005
	Self-Employed	-.20424	.17892	.784
	Professional	-.05011	.20959	.999
	Student	.41289*	.14765	.043

ISBN: 978-93-343-1044-3

Private Employee	Govt. Employee	-.02817	.12168	.999
	Self-Employed	.20865	.17505	.756
	Professional	.36278	.20629	.400
Govt. Employee	Student	.44106*	.12720	.005
	Private Employee	.02817	.12168	.999
	Self-Employed	.23682	.15818	.565
	Professional	.39096	.19219	.252
Self-Employed	Student	.20424	.17892	.784
	Private Employee	-.20865	.17505	.756
	Govt. Employee	-.23682	.15818	.565
	Professional	.15414	.22972	.963
Professional	Student	.05011	.20959	.999
	Private Employee	-.36278	.20629	.400
	Govt. Employee	-.39096	.19219	.252
	Self-Employed	-.15414	.22972	.963

* The mean difference is significant at the 0.05 level.

The table 5 shows that as for Behavioural Intention to use AIFA, there is significant differences were found between student group and private employee group and also between student group and govt employee group. However, there are no significant differences when comparing other groups on the basis of occupation.

VII. CONCLUSION

The present study focuses on examining the impact of occupation on the Customer's adoption factors of AI-driven financial assistant as well as on the Behavioural Intention to use AI-driven financial assistant. The overall result of the present study indicates that on the basis of occupation, there is significant difference found in customer's adoption factors of Personal Innovativeness while there is no significant difference found in Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Trust. In addition to this, behavioural intention to use AIFA also differentiate among different groups on the basis of occupation. The study also depicts that Govt. employees are more inclined towards AIFA as compared to students as well as Private employees are also more inclined towards AIFA as compared to students.

By considering the above results, the banks can make their strategies to better target the customers to improve their perceptions regarding intention to use AI driven financial assistant with the help of which customers can resolve their queries in a much better way. The results of present study on AI-driven financial assistant services provide valuable insights that help banks better understand their customers. By analyzing how customers interact with these systems, banks can refine their strategies to improve user engagement, boost customer loyalty and offer more relevant and effective financial solutions. Ultimately, this technology not only enhances the customer experience but also enables banks to stay competitive in a rapidly evolving financial landscape.

VIII. LIMITATIONS OF THE STUDY AND DIRECTIONS FOR FUTURE WORK

The present work is limited by considering only one demographic variable due to time constraints. The further study can also be conducted by taking into account the other demographic variables of the study. The scope of the present study is limited to Haryana only. Future work can be done in other states of the country. The study can also be categorized as per geographical locations of the entire country such as Eastern, Western, Northern as well as Southern part of the county. The future study can also be conducted by considering other customer adoption factors as well. The research can also be conducted to observe how AI based services are adopted by customers of public and private sector banks. The research can also be conducted to observe how AI based services are adopted by customers of banks across rural and urban areas.

IX. REFERENCES

[1] Alagarsamy, S., & Mehrolia, S. (2023). Exploring chatbot trust: Antecedents and behavioural outcomes. Heliyon, 9 (5), e16074.

[2] Bhattacharya, C., & Sinha, M. (2022). Role of Artificial Intelligence in Banking for Leveraging Customer Experience. Australasian Accounting, Business and Finance Journal, 16(5). https://doi.org/10.14453/aabfj.v16i5.07

[3] Cheng, Y., & Jiang, H. (2020). How Do AI-driven Chatbots Impact User Experience? Examining Gratifications, Perceived Privacy Risk, Satisfaction, Loyalty, and Continued Use. Journal of Broadcasting and Electronic

ISBN: 978-93-343-1044-3

Media, 64(4), 592–614. https://doi.org/10.1080/08838151.2020.1834296

[4] Dantsoho, M. A., Ringim, K. J., & Kura, K. M. (2021). The Relationship between Artificial Intelligence (AI) Quality, Customer Preference, Satisfaction and Continuous Usage Intention of e-Banking Services. Indonesia Business Review, 4(1), 24–43.

[5] Elkhatibi, Y., Guelzim, H., & Benabdelouahed, R. (2024). Factors Influencing the Adoption of AI-Powered Chatbots in the Moroccan Banking Sector: An Extended UTAUT Model. *Journal of Logistics, Informatics and Service Science*, *11*(7), 559-585.

[6] Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2. *Interactive Technology and Smart Education*, *14*(4), 329-348.

[7] Goli, M., Sahu, A. K., Bag, S., & Dhamija, P. (2023). Users' acceptance of artificial intelligence-based chatbots: an empirical study. International Journal of Technology and Human Interaction (IJTHI), 19(1), 1-18. Chicago

[8] Golubev, A., Ryabov, O., & Zolotarev, A. (2020). Digital transformation of the banking system of Russia with the introduction of blockchain and artificial intelligence technologies. IOP Conference Series: Materials Science and Engineering, 940(1). https://doi.org/10.1088/1757-899X/940/1/012041

[9] Gunasinghe, A., Hamid, J. A., Khatibi, A., & Azam, S. F. (2020). The adequacy of UTAUT-3 in interpreting academician's adoption to e-Learning in higher education environments. Interactive Technology and Smart Education, 17(1), 86-106. Chicago

[10] Gündeş, F., & Sazkaya, M. K. (2018). A Study on Consumers' Adoption and Behavioural Intention Towards Innovative Banking Products. Kafkas Universitesi Veteriner Fakultesi Dergisi, 9, 101–130. https://doi.org/10.9775/kauiibfd.2018.005

[11] Kelly, S., Kaye, S. A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. Telematics and Informatics, 77, 101925. Chicago

[12] Maulani, E., & Handayani, S. S. (2023). Analysis of the Application of the Unified Theory of Acceptance and Use of Technology 3 (UTAUT-3) Model on Intention and Use Behavior of Users of Mobile Banking Applications in the Jabodetabek Region. Int. J. Soc. Sci. Hum. Res, 6(09), 5465-5475. Chicago

[13] Mishra, S. & Ghumre, N. V. (2020). Consumer Behaviour: Move Towards Digital Payment in Rural Environment. Purakala (UGC Care Journal)31(13),169-180.

[14] Mogaji, E., Balakrishnan, J., Nwoba, A. C., & Nguyen, N. P. (2021). Emerging-market consumers' interactions with banking chatbots. Telematics and Informatics, 65, 101711. Chicago

[15] Patil, K., & Kulkarni, M. S. (2019). Artificial intelligence in financial services: Customer chatbot advisor adoption. International Journal of Innovative Technology and Exploring Engineering, 9(1), 4296–4303. https://doi.org/10.35940/ijitee.A4928.119119

[16] Qureshi, O. A., Wilkins, S., & Iqbal, H. (2024, March). Chatbots: Can They Satisfy Customers in the Banking Sector?. In BUiD Doctoral Research Conference 2023: Multidisciplinary Studies (pp. 360-376). Cham: Springer Nature Switzerland. Chicago

[17] Richad, R., Vivensius, V., Sfenrianto, S., &Kaburuan, E. R. (2019). Analysis of Factors Influencing Millennial's Technology Acceptance of Chatbot in the Banking Industry in Indonesia. International Journal of Civil Engineering and Technology, 10(04), 1270–1281. https://doi.org/10.34218/IJM.10.3.2019.011

[18] R., V., & Ravi, H. (2021). Innovation in banking: fusion of artificial intelligence and blockchain. Asia Pacific Journal of Innovation and Entrepreneurship, 15(1), 51–61. https://doi.org/10.1108/apjie-09-2020-0142

[19] Sivathanu, B. (2019). Adoption of digital payment systems in the era of demonetization in India: An empirical study. Journal of Science and Technology Policy Management, 10(1), 143-171. Chicago

[20] Soni, V. D. (2019). ROLE OF ARTIFICIAL INTELLIGENCE IN COMBATING CYBER THREATS IN BANKING. International Engineering Journal For Research & Development, 4(1), 1–7.

[21] Trivedi, J. (2019). Examining the Customer Experience of Using Banking Chatbots and Its Impact on Brand Love: The Moderating Role of Perceived Risk. Journal of Internet Commerce, 18(1), 91–111. https://doi.org/10.1080/15332861.2019.1567188

[22] Venkatesan, S., & Sumathi, N. (2019). Technology Acceptance of Artificial Intelligence in Banking and its Impact on Banking Efficiency. International Journal of Innovative Technology and Exploring Engineering, 8(7C2), 371–374.

[23] Vijai, C. (2018). ARTIFICIAL INTELLIGENCE IN INDIAN BANKING SECTOR: CHALLENGES AND OPPORTUNITIES. International Journal of Advanced Research, 7(5), 1581–1587. https://doi.org/10.21474/IJAR01/8987

[24] Yadav, P., Gupta, P., Rai, P., Naik, N., & Kasip, K. (2023). Exploring the factors influencing the adoption and continuous engagement in unlocking the potential of technology driven chatbots in banking and financial institutions. Engineered Science, 28, 1054.

[25] Yusof, N. A. M., Anthonysamy, L., Shahimi, W. R. M. A., Tun-Pin, C., & Apadore, K. (2023). Reshaping banking: the use of chatbots for customer services. Int J Acc, 8(48), 135-154. Chicago

ISBN: 978-93-343-1044-3