

**Master's Thesis submitted in fulfilment of the requirements for
the Master's Degree**

Major: E-Business

THEME:

**THE IMPACT OF ARTIFICIAL INTELLIGENCE ON
USER EXPERIENCE THROUGH A MOBILE
APPLICATION AMONG THE YOUNG GENERATION**

CASE: *The My Ooredoo Mobile Application: Ooredoo Algeria*

Submitted by:

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- Mr. Chawki Salim TOUIEB
(Ooredoo Supervisor)

Academic Year

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DEDICATION

By the grace of Allah, the Most Gracious, the Most Merciful, this modest work has come to light. I dedicate it:

To my dear father and my dear mother, whose love, patience and unwavering support have been the foundation of everything I have accomplished, no words could ever repay what I owe you;

To my brothers, Ilies and Fares, and to my sister, Ines, for their affection, their encouragement and their constant presence at my side;

To all my family, for their prayers and their confidence in me throughout this journey;

To my friends, Adel, Sidali, Younes, Mohammed, Habib, Kamel, Amine, Adlen, Wassim, Rami, Talal, Aymen, Wael, Abdelkader, Mohammed, Ziad, Talal, Taha, Sidali. Hamza, Sadki, for their loyalty and for every moment shared along the way;

To my teachers and to my classmates of this promotion, who accompanied me through these years of study;

And finally, to myself, in recognition of the effort, the perseverance and the determination that carried this work through to completion.

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Finally, I wish to thank the members of the jury for the honour of agreeing to read and evaluate this work, and my family and friends, whose unfailing support carried me through the demands of this research.

LIST OF ABBREVIATIONS

Abbr.	Title
AI	Artificial Intelligence
ANPDP	Autorité Nationale de Protection des Données à Caractère Personnel
ARPCE	Autorité de Régulation de la Poste et des Communications Électroniques
ARPU	Average Revenue Per User
AVE	Average Variance Extracted
B2B / B2C	Business-to-Business / Business-to-Consumer
BCa	Bias-Corrected and accelerated (bootstrap)
CASA	Computers Are Social Actors (paradigm)
CB-SEM	Covariance-Based Structural Equation Modelling
CES	Customer Effort Score
CR	Composite Reliability
CSAT	Customer Satisfaction (score)
CVM	Customer Value Management
DPIA	Data Protection Impact Assessment
DPO	Data Protection Officer
E-S-QUAL	Electronic Service Quality (scale)
GDPR	General Data Protection Regulation
GSM	Global System for Mobile Communications
HCI	Human-Computer Interaction
HTMT	Heterotrait-Monotrait ratio
IoT	Internet of Things
ISO	International Organization for Standardization
KPI	Key Performance Indicator
LLM	Large Language Model
ML	Machine Learning
M-S-QUAL	Mobile Service Quality (scale)
NBA	Next-Best-Action
NBO	Next-Best-Offer
NLP	Natural Language Processing
NPS	Net Promoter Score
OTP	One-Time Password
PLS-SEM	Partial Least Squares Structural Equation Modelling
PSP	Payment Service Provider
QoS	Quality of Service
RFM	Recency, Frequency, Monetary (segmentation)
SEM	Structural Equation Modelling

Abbr.	Title
SERVQUAL	Service Quality (scale)
SIM	Subscriber Identity Module
SST	Self-Service Technology
TAM	Technology Acceptance Model
UI	User Interface
UTAUT (2)	Unified Theory of Acceptance and Use of Technology (extended)
UX	User Experience
VIF	Variance Inflation Factor
WTA	Wataniya Télécom Algérie

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RÉSUMÉ

L'essor de l'intelligence artificielle a transformé la relation entre les opérateurs de télécommunications et leurs clients, faisant de l'application mobile le principal point de contact du parcours client. En Algérie, marché en pleine maturation numérique, Ooredoo a bâti une part importante de sa stratégie concurrentielle autour d'une architecture d'expérience client pilotée par l'IA. Ce mémoire examine dans quelle mesure l'intégration de l'intelligence artificielle au sein de l'application My Ooredoo améliore l'expérience des utilisateurs algériens. Trois hypothèses structurent l'analyse : l'effet des mécanismes d'IA sur l'efficacité perçue de la navigation (H1), l'effet du dispositif conversationnel sur la qualité de l'expérience (H2) et l'effet de la personnalisation pilotée par l'IA sur la fidélité (H3). La recherche mobilise un design mixte explicatif séquentiel : une phase quantitative (163 répondants) traitée par modélisation par équations structurelles (PLS-SEM) avec bootstrap à 5 000 ré-échantillons, suivie d'une phase qualitative (quatre entretiens d'experts) analysée selon le protocole thématique de Braun et Clarke. Les hypothèses H1 et H3 sont confirmées, tandis que la H2 demeure non concluante : H1 ($\beta = +0,545$), H2 ($\beta = +0,398$, statistiquement significative mais à interpréter avec prudence) et H3 ($\beta = +0,587$). Les hypothèses H1 et H3 sont significatives au seuil de 0,1 % ; la H2, bien que significative, ne peut être confirmée, le module conversationnel n'ayant été mesuré à partir d'une expérience réelle que pour une minorité de l'échantillon. La principale limite de l'étude tient à un échantillon restreint et non probabiliste, qui restreint la portée de la généralisation des résultats. La recherche débouche sur cinq recommandations opérationnelles pour Ooredoo Algérie.

Mots-clés : intelligence artificielle ; expérience utilisateur ; application mobile ; agent conversationnel ; personnalisation ; fidélité ; PLS-SEM ; Ooredoo Algérie.

ABSTRACT

The rise of artificial intelligence has reshaped the relationship between telecommunications operators and their customers, turning the mobile application into the primary touchpoint of the customer journey. In Algeria, a market still maturing digitally, Ooredoo has built a substantial part of its competitive strategy around an AI-driven customer-experience architecture. This dissertation examines the extent to which the integration of artificial intelligence within the My Ooredoo application improves the experience of Ooredoo Algeria's users. Three hypotheses structure the analysis: the effect of AI mechanisms on perceived navigation efficiency (H1), the effect of the conversational module on the quality of user experience (H2), and the effect of AI-driven personalisation on user loyalty (H3). The study adopts a sequential explanatory mixed-methods design: a quantitative phase (163 respondents) analysed through Partial Least Squares Structural Equation Modelling (PLS-SEM) with 5,000-resample bootstrapping, followed by a qualitative phase (four expert interviews) analysed through Braun and Clarke's thematic protocol. Two of the three hypotheses are supported: H1 ($\beta = +0.545$) and H3 ($\beta = +0.587$), each significant at the 0.1% level. The chatbot path (H2: $\beta = +0.398$) is positive and statistically significant, yet the evidence is not robust enough to confirm the hypothesis, since roughly two-thirds of respondents had never knowingly used the conversational module; H2 is therefore reported as inconclusive and interpreted with caution, pending re-examination on a larger probabilistic sample. The principal limitation of the study is its small, non-probabilistic sample, which restricts the generalisation of the findings. The qualitative phase specifies the mechanisms behind the effects observed, and the research yields five actionable recommendations for Ooredoo Algeria's digital teams.

Keywords: artificial intelligence; user experience; mobile application; conversational agent; personalisation; loyalty; PLS-SEM; Ooredoo Algeria.

ملخص

شهدت العلاقة بين متعاملي الاتصالات وزبائنهم تحولاً عميقاً مع صعود الذكاء الاصطناعي، إذ أصبح التطبيق المحمول نقطة التماس الرئيسية في مسار العميل. وفي الجزائر، وهي سوق لا تزال في طور النضج الرقمي، بنت مؤسسة Ooredoo جزءاً جوهرياً من استراتيجيتها التنافسية حول هندسة تجربة العميل مدفوعة بالذكاء الاصطناعي. تبحث هذه المذكرة في المدى الذي يُحسّن فيه دمج الذكاء الاصطناعي ضمن تطبيق My Ooredoo تجربة مستخدمي Ooredoo الجزائر. تنتظم الدراسة حول ثلاث فرضيات: أثر آليات الذكاء الاصطناعي في الفعالية المُدرَكة للتصفّح (الفرضية الأولى)، وأثر الوحدة الحوارية في جودة تجربة المستخدم (الفرضية الثانية)، وأثر التخصيص المدفوع بالذكاء الاصطناعي في ولاء المستخدمين (الفرضية الثالثة). اعتمدت الدراسة تصميماً مختلطاً تفسيريّاً تتابعياً: مرحلة كمّية (163 مستجيباً) غُولِجت بنمذجة المعادلات البنوية بطريقة المربّعات الصغرى الجزئية (PLS-SEM) مع إعادة معاينة بالتمهيد (Bootstrap) على 5000 عيّنة، تَلْتَمُها مرحلة نوعية (أربع مقابلات مع خبراء) حُلِّلت وفق البروتوكول الموضوعاتي لـ Clarke و Braun. أَكَّدَت النتائج الفرضيتين الأولى والثالثة وأبقت الفرضية الثانية غير حاسمة: الفرضية الأولى ($\beta = +0.545$)، والفرضية الثانية ($\beta = +0.398$)، والفرضية الثالثة ($\beta = +0.587$)، والفرضيتان الأولى والثالثة دالّتان عند مستوى 0.1%. أمّا الفرضية الثانية فهي دالّة إحصائياً غير أنّها تظلّ غير حاسمة، إذ لم يُقَسَّ المساعد المحادثي من تجربة فعلية إلا لدى أقلية من العيّنة، فتُفسَّر بحذرٍ وتستلزم إعادة فحصٍ على عيّنة احتمالية أكبر. وتتمثّل أبرز محدوديات الدراسة في صغر حجم العيّنة وطابعها غير الاحتمالي، ممّا يحدّ من تعميم النتائج. وقد حدّدت المرحلة النوعية الآليات الكامنة وراء هذه الآثار، وخلصت الدراسة إلى خمس توصيات عملية موجّهة للفرق الرقمية في Ooredoo الجزائر.

الكلمات المفتاحية: الذكاء الاصطناعي؛ تجربة المستخدم؛ التطبيق المحمول؛ الوكيل المحادثاتي؛ التخصيص؛ الوفاء؛ نمذجة المعادلات البنوية (PLS-SEM)؛ Ooredoo الجزائر.

GENERAL INTRODUCTION

The relationship between people and the digital systems they depend on has rarely carried higher stakes than it does today. For a growing share of the world's population, the mobile application is no longer a convenience layered on top of a service; it is the service. Nowhere is this more visible than in telecommunications, where the operator's application has become the first and frequently the only channel through which subscribers recharge their accounts, manage their plans, resolve billing disputes, and seek support. The quality of that encounter, what the research literature calls user experience, has consequently moved from a peripheral design concern to a decisive determinant of satisfaction, retention, and competitive advantage.

Two forces have converged to sharpen this shift. The first is the maturation of artificial intelligence, which has migrated from the research laboratory into the core of service delivery: conversational agents now handle millions of customer interactions, machine-learning models anticipate needs and detect anomalies in real time, and natural-language processing lets users interact in ordinary speech rather than through rigid menus. The second is the rapid digitalisation of emerging markets, where operators are deploying these capabilities at speed even as the surrounding infrastructure, regulatory frameworks, and digital literacy of users continue to evolve. The intersection of the two raises a question that is at once theoretical and intensely practical: when artificial intelligence is woven into a mobile service, what actually happens to the experience of the people who use it?

Algeria offers a particularly instructive vantage point. Its mobile market is a regulated triopoly in which Ooredoo Algeria operating under the legal designation *Wataniya Télécom Algérie* has differentiated itself through a digital strategy built explicitly around AI-driven customer-experience architecture. Behind its My Ooredoo application sits a Customer Value Management (CVM) department running a portfolio of production machine-learning models churn prediction, Next-Best-Offer, Next-Best-Action and multi-SIM detection among them while a conversational agent operates at the visible front line. This asymmetry between sophisticated back-end intelligence and a comparatively modest front-end interface makes Ooredoo Algeria an unusually rich field in which to study how AI reshapes user experience in a still-maturing digital economy.

Motives for the choice of subject

On the subjective side, the topic sits at the meeting point of two of the author's sustained interests digital management and the practical workings of artificial intelligence and the

opportunity to examine a leading national operator from the inside, through privileged access to its Customer Value Management team, made the My Ooredoo case both feasible and genuinely motivating.

On the objective side, the subject responds to a visible gap in the literature and to a concrete sectoral need. International research on AI and user experience is concentrated overwhelmingly in Western and East-Asian e-commerce settings; the Algerian and broader Maghreb context remains markedly under-investigated, even though it presents conditions multilingual code-switching, prepaid dominance, uneven digital literacy that established models do not straightforwardly accommodate. The subject also aligns directly with the digital-economy vocation of ESGEN.

Research problem

To what extent does the integration of artificial intelligence into the My Ooredoo mobile application improve the user experience of Ooredoo Algeria's customers?

Secondary research questions

- Q1. To what extent do the AI mechanisms embedded in the application affect the efficiency with which users navigate it and complete their tasks?
- Q2. To what extent does the chatbot and virtual-assistant module shape the overall quality of the user experience?
- Q3. To what extent does AI-driven personalisation influence users' behaviour, and in particular their loyalty toward the application?

Research hypotheses

- H1.** The integration of AI mechanisms within the My Ooredoo application exerts a positive and significant effect on the perceived efficiency of navigation.
- H2.** The deployment of the chatbot and virtual-assistant module exerts a positive and significant effect on the overall quality of the user experience.
- H3.** The adoption of AI-driven personalisation features exerts a positive and significant effect on user loyalty toward the application.

Research methodology and tools

The study adopts a positivist, deductive stance and a **sequential explanatory mixed-methods design**. A quantitative phase first tests the structural relationships among the constructs, after

which a qualitative phase interprets the mechanisms the statistics leave open. The quantitative instrument is a structured, self-administered questionnaire of thirty-six items returning 163 valid responses, analysed through PLS-SEM (specified in SmartPLS 4; estimation and 5,000-resample bootstrap inference in Python). The qualitative instrument is a semi-structured expert interview guide administered to four informants selected through maximum-variation sampling, analysed through Braun and Clarke's six-phase thematic protocol. The two strands are integrated through a joint display.

Structure of the dissertation

The dissertation is organised into two chapters. **Chapter I** builds the theoretical framework, tracing user experience from its conceptual foundations to its mobile and telecom-specific dynamics, establishing what artificial intelligence is and how it is deployed in service contexts, and bringing the two streams together to derive the hypotheses. **Chapter II** presents the empirical investigation: its first section situates Ooredoo Algeria within the national market and documents the concrete instruments of its digital transformation, while its second section sets out the methodology, tests the three hypotheses, integrates the quantitative and qualitative evidence, and draws out the managerial implications. A general conclusion then returns to the problem and opens onto future research.

CHAPTER I

THEORETICAL FRAMEWORK: THE IMPACT OF ARTIFICIAL INTELLIGENCE ON USER EXPERIENCE THROUGH A MOBILE APPLICATION

A Conceptual and Analytical Review

General Introduction to Chapter I

This theoretical chapter establishes the conceptual and analytical foundations for the empirical investigation that follows, proceeding through three cumulative sections. Section 1 examines user experience as a discipline and its distinctive demands in mobile and telecommunications contexts, Section 2 examines artificial intelligence together with its core technologies and enterprise deployment patterns, and Section 3 brings the two together to analyse how AI deployment reshapes user experience and to derive the hypotheses of the study. Together the three sections build the theoretical vocabulary, the analytical frameworks and the hypotheses that the empirical chapter operationalises and tests using interview and questionnaire data collected from users of the My Ooredoo mobile application in Algeria.

SECTION 1

USER EXPERIENCE IN MOBILE APPLICATIONS AND TELECOM SERVICES

This section concentrates on three building blocks: the conceptual foundations of user experience, the frameworks through which that experience is evaluated, and the telecom-specific dynamics that shape it in mobile-service environments.

1.1 Understanding User Experience: Conceptual Foundations and Core Dimensions

Human experience, in its broadest sense, encompasses the cognitive, emotional, and behavioral responses that arise whenever people engage with their surroundings, objects, and other persons. Hassenzahl establishes that this experience is shaped by context, personal expectations, emotional interpretation, and the functional quality of the objects or systems involved.¹ When this fundamental capacity enters a commercial setting, it transforms into what Meyer and Schwager term *customer experience*: the totality of exchanges between a customer and an organization, integrating both practical outcomes and affective responses such as trust, satisfaction, or frustration.² In a telecom mobile application context, an application is assessed not only by whether a bill payment succeeds, but equally by whether the user felt confident and unencumbered throughout the process.

User experience sits within customer experience but narrows the lens to a specific interaction with a product, system, or service. ISO 9241-210 (2019) defines it as *a person's perceptions and responses that result from the use and/or anticipated use of a product, system or service*,³ What makes this formulation particularly valuable is its temporal scope: it recognizes that user experience extends beyond the moment of interaction itself, encompassing both the

¹HASSENZAHN (Marc), *Experience Design: Technology for All the Right Reasons*, Synthesis Lectures on Human-Centered Informatics, Morgan & Claypool Publishers, San Rafael, 2010, p. 40.

²MEYER (Christopher) & SCHWAGER (André), "Understanding Customer Experience," *Harvard Business Review*, vol. 85, no. 2, 2007, p. 118.

³ISO, ISO 9241-210:2019, *Ergonomics of Human-System Interaction Part 210: Human-Centred Design for Interactive Systems*, International Organization for Standardization, Geneva, 2019, p. 3.

expectations individuals form before they engage with a system and the reflections, they carry with them long after use concludes.

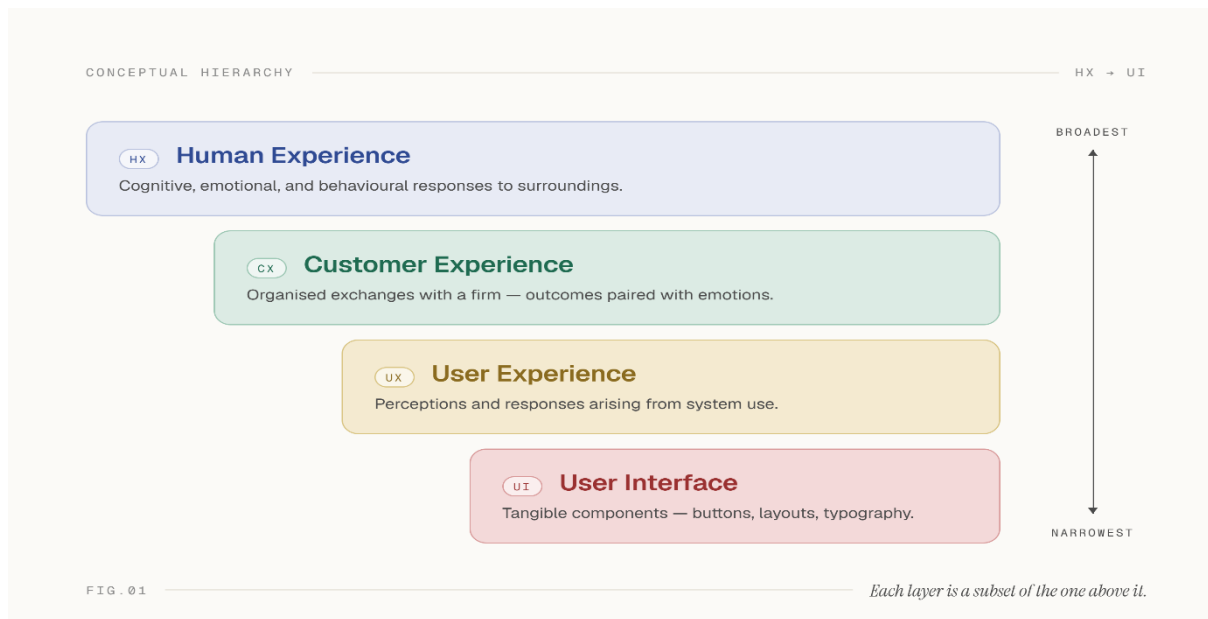
Hassenzahl and Tractinsky (2006) locate UX at the convergence of three forces: the user's internal state, the system's characteristics, and the context of interaction.¹ UX is therefore situational and subjective, varying across individuals and contexts. Where customer experience is relationship-centred, user experience is interaction-centred.

User interface (UI) constitutes the tangible, visible layer through which interaction occurs: buttons, menus, layouts, typography, and colour systems that users directly encounter and manipulate. While UI is undoubtedly essential for usability, it constitutes only a single layer within the far more expansive territory of user experience. The critical distinction lies in scope: UI concerns itself with making interaction possible and efficient, whereas UX encompasses the fuller emotional and psychological dimension of the experience: how a product makes someone feel, whether it delivers aesthetic pleasure, and the perceived value it generates over time. This boundary between UI and UX becomes sharper when we recognise the difference between pragmatic and hedonic dimensions of design.

Pragmatic qualities functionality, efficiency, predictability is what UI primarily addresses: the system must work as intended.² Yet user experience, by definition, extends into hedonic territory: the desire for stimulation, the sense of identity and belonging a product cultivates, the simple pleasure of using something well-designed. A beautifully crafted interface may serve pragmatic needs excellently, but if it fails to engage hedonic dimensions if it feels sterile, impersonal, or emotionally hollow the overall experience remains incomplete. This is why two products can be equally *usable* yet differ profoundly in how people *experience* them.

¹HASSENZAHL (Marc) & TRACTINSKY (Noam), "User experience – a research agenda," Behaviour & Information Technology, vol. 25, no. 2, 2006, p. 93.

²HASSENZAHL (Marc), op. cit., p. 40.

Figure 1: Conceptual hierarchy

Source: Author's elaboration based on Hassenzahl (2010, p. 40); Meyer & Schwager (2007, p. 118); ISO 9241-210 (2019); Nielsen (1993, p. 45).

1.1.1 Core Dimensions of User Experience

The UX literature identifies four dimensions that jointly characterize quality along a pragmatic-hedonic axis. Usability constitutes the pragmatic foundation, encompassing learnability, efficiency, error recovery, and the overall sense of confidence a system produces.¹ Usefulness connects the system's capabilities to the user's real goals; Garrett notes that even technically competent systems do not lead to real UX if they do not address real problems.²

Emotional engagement encompasses the feelings of satisfaction, delight, trust, and motivation that arise during interaction. Hassenzahl argues that *users' emotions, including pleasure, trust, and engagement, strongly influence the overall experience*.³ Perceived value integrates functional, emotional, and hedonic considerations into a comprehensive judgement of whether an interaction was worthwhile. The value represents the accumulated quality of the experience

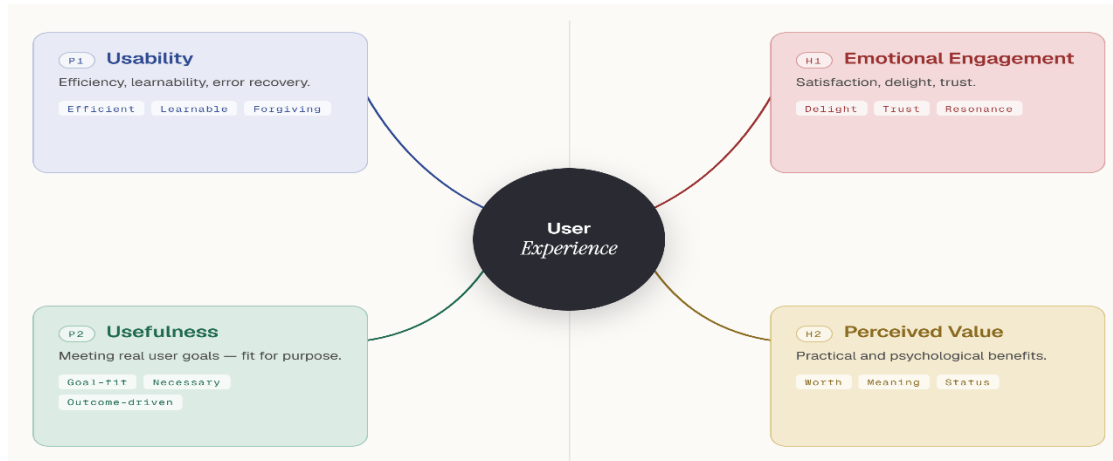
¹Hassenzahl, M. (2003). The Thing and I: Understanding the Relationship Between User and Product. In: Blythe, M.A., Overbeeke, K., Monk, A.F., Wright, P.C. (eds) *Funology*. Human-Computer Interaction Series, vol 3. Page 33.

²GARRETT (Jesse James), *The Elements of User Experience: User-Centered Design for the Web and Beyond*, 2nd edn, New Riders, Berkeley, 2011, p. 20.

³HASSENZAHN (Marc), op. cit., p. 40.

assessed against the effort, time, and cost invested.¹ Together, these four dimensions position UX as simultaneously pragmatic (usability, usefulness) and hedonic (emotion, value).

Figure 2: Core dimensions of user experience



Source: Author's elaboration based on Nielsen (1993, p. 15); Garrett (2011, p. 20); Hassenzahl (2010, p. 40); Law et al. (2009, p. 125).

1.2 Historical and Strategic Perspective of User Experience

1.2.1 Origins and Emergence of the UX Concept

User experience as a distinct field of inquiry emerged from within usability research, itself a product of the HCI and ergonomics traditions that flourished in the 1980s. Early work in this period concentrated on a narrower problem: how to reduce system errors and maximise operational ease of use.² The intellectual landscape shifted decisively in the early 1990s when Don Norman, working at Apple, reframed the entire enterprise. Rather than treating UX as a technical problem of interface efficiency, Norman advanced a far more expansive vision: user experience as a construct encompassing *every* dimension of a person's encounter with a system industrial design, interface layout, interaction dynamics, documentation, even the emotional response the product provokes.³

¹LAW (Effie Lai-Chong), ROTO (Virpi), HASSENZAHN (Marc), VERMEEREN (Arnold) & KORT (Joke), "Understanding, scoping and defining user experience: a survey approach," Proceedings of CHI 2009, ACM, Boston, 2009, p. 125.

²DIX (Alan), FINLAY (Janet), ABOWD (Gregory D.) & BEALE (Russell), Human-Computer Interaction, 3rd edn, Pearson Education, Harlow, 2004, p. 8.

³NORMAN (Donald A.), The Design of Everyday Things, Basic Books, New York, 2002, p. 9.

This conceptual enlargement proved consequential. It opened the field to considerations that earlier usability research had bracketed: Why does one product feel delightful while another, functionally equivalent, feels sterile? How do emotional and aesthetic dimensions shape not just satisfaction but loyalty and willingness to recommend? Building on this foundation, Hassenzahl articulated what would become central to contemporary UX theory: the recognition that, from its earliest theorization, user experience necessarily encompasses both pragmatic dimensions (usability, functionality, task efficiency) and hedonic dimensions (stimulation, identification with the product's values, the pleasure of aesthetic and emotional engagement).¹ This integration of pragmatic and hedonic concerns transformed UX from a narrowly functional discipline into a comprehensive framework accounting for the full spectrum of how humans relate to technology.

1.2.2 Evolution of UX Thinking

Following its emergence from the narrower concerns of interface design, UX expanded steadily to encompass the full experiential complexity of human-technology interaction. Central to this expansion was Hassenzahl's contribution: the theoretical recognition that experience quality depends equally on hedonic dimensions stimulation, identification, positive emotion as on pragmatic usability.² Hassenzahl (2003) establishes that experience is not a fixed property inherent to a system but an *emergent phenomenon* arising from the dynamic interplay of the person, the system's characteristics, and the context of their encounter. This theoretical move opened the field to explain why functionally identical systems generate divergent experiences across individuals and situations.³ Morville extended this framework by insisting that UX encompasses something even broader: the pursuit of interactions that are simultaneously meaningful, valuable, and enjoyable a formulation that positioned UX not as a technical discipline but as a humanistic endeavor.⁴ The theoretical predictions have been confirmed by empirical research in telecom service environments, where engagement, emotion, perceived

¹HASSENZAHL (Marc), "The thing and I: Understanding the relationship between user and product," in BLYTHE (M.) et al. (eds.), *Funology: From Usability to Enjoyment*, Kluwer Academic Publishers, Dordrecht, 2003, p. 93.

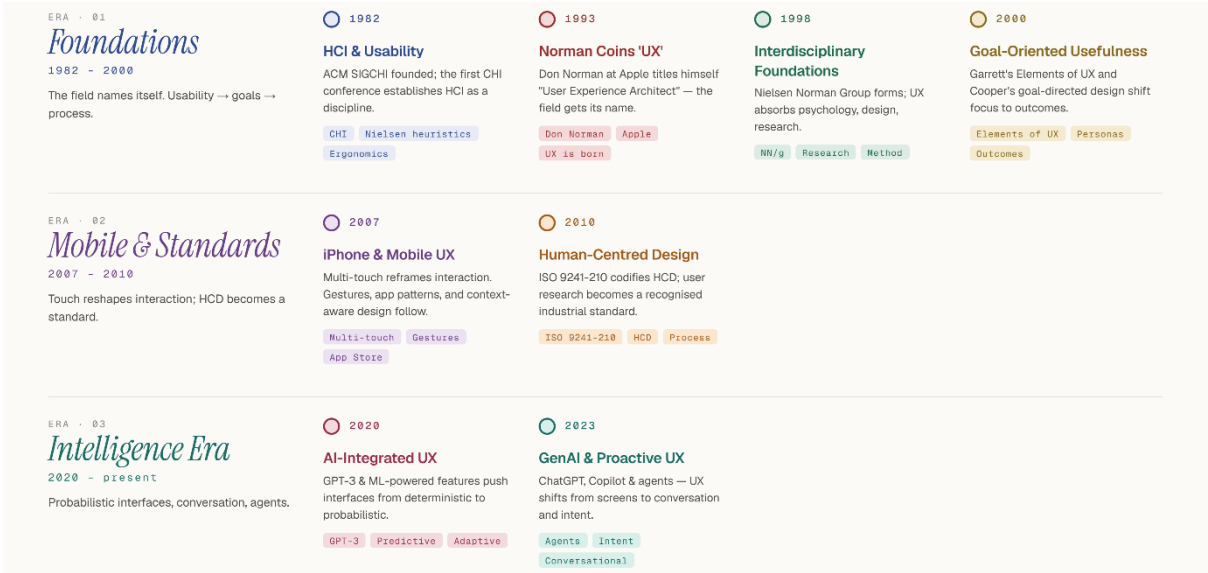
²HASSENZAHL (Marc) (2010), op. cit., p. 40.

³HASSENZAHL (Marc) (2003), op. cit., p. 93.

⁴MORVILLE (Peter), "User Experience Design," Semantic Studios, 2004, available at: https://semanticstudios.com/user_experience_design/ [accessed: 26 February 2026, 14:55].

value, and usability function not as isolated dimensions but as deeply interdependent variables shaping the overall quality of the service relationship.¹

Figure 3: Evolution of user experience



Source : Author's elaboration based on Dix et al. (2004, p. 8); Norman (2002, p. 9); Hassenzahl (2003; 2010); ISO 9241-210 (2019).

1.2.3 User Experience as a Strategic and Competitive Lever

By the 2010s, organizations had fundamentally reframed UX from a technical concern to a strategic asset one capable of directly influencing market position, customer loyalty, and revenue. The foundations for this shift were intellectual as well as commercial. Norman established that design quality functions as a fundamental competitive differentiator: products that work intuitively and coherently outcompete those offering marginal functional advantages but requiring cognitive effort to use.² Yet the competitive advantage extends further still. Hassenzahl illuminated the affective dimension that elevates UX beyond pragmatic utility: experiences capable of generating genuine emotional attachment create competitive advantages anchored not in technological superiority but in the psychological value users attribute to their relationship with the product.³ This insight proved decisive it suggested that lasting competitive advantage emerges not from feature parity but from the *felt experience* of engagement itself.

¹HOSSAIN (Md. Alamgir) et al., "User experience and engagement in telecom mobile applications," Telecommunications Policy, vol. 48, no. 5, 2024, p. 3.
²NORMAN (Donald A.), op. cit., p. 9.
³HASSENZAHN (Marc) (2010), op. cit., p. 40.

The theoretical case for UX as a strategic asset has been systematically validated through empirical research in digital and telecom services: applications with superior UX consistently demonstrate higher retention rates and customer satisfaction, outcomes that translate directly into measurable improvements across key business metrics most notably Net Promoter Score.¹ This empirical consistency is reinforced by international standards; ISO 9241-210 formally establishes that human-centred design approaches directly correlate with organisational performance outcomes.² The evidence thus converges: organisations that prioritize UX are not pursuing an aesthetic luxury but investing in a strategic mechanism for competitive advantage.

1.3 User Experience in Mobile Applications

The launch of the iPhone in 2007 marked a decisive paradigm shift. Norman draws attention to the centrality of context in shaping interaction quality,³ and mobile contexts introduced conditions interruptions, distractions, multitasking, fragmented attention that rendered desktop UX principles insufficient.

1.3.1 Mobile UX Fundamentals and Specificities

Mobile UX operates under fundamentally different constraints than desktop interaction, constraints that reshape nearly every design decision. The small screen demands ruthless content prioritization; every pixel carries weight. Touch-based interfaces require sufficiently large targets and intuitive gestural conventions that users intuitively understand without instruction. Context becomes paramount: interactions occur in transit, in crowds, under divided attention and environmental noise. Performance sensitivity is acute; mobile users maintain an extraordinarily low tolerance for delays; seconds matter. Sessions themselves are brief, goal-oriented bursts rather than sustained engagement, necessitating streamlined task flows that complete quickly.

These technical constraints converge on a single, demanding discipline: the art of exclusion. Nielsen and Budiu identify this as the core challenge determining with precision what to omit,

¹DE KEYSER (Arne) et al., "Customer experience management in digital services," *Journal of Retailing and Consumer Services*, vol. 83, 2025, p. 4.

²ISO, op. cit., p. 5.

³NORMAN (Donald A.), *The Design of Everyday Things*, Revised and Expanded edn, Basic Books, New York, 2013, p. 11.

what to remove, what to leave unsaid in order to preserve clarity and focus.¹ This is not a mobile-specific insight, however. Norman frames it within a broader philosophical principle: all interaction is inherently contextual. Mobile does not introduce this principle; it simply makes it impossible to ignore.² The screen size, the gestural vocabulary, the distracted user, the fragmented session together they eliminate any possibility of hiding behind feature abundance or visual ornament. Mobile design forces the designer to confront an uncompromising truth: clarity emerges not from addition but from disciplined subtraction.

1.3.2 The Mobile User Journey

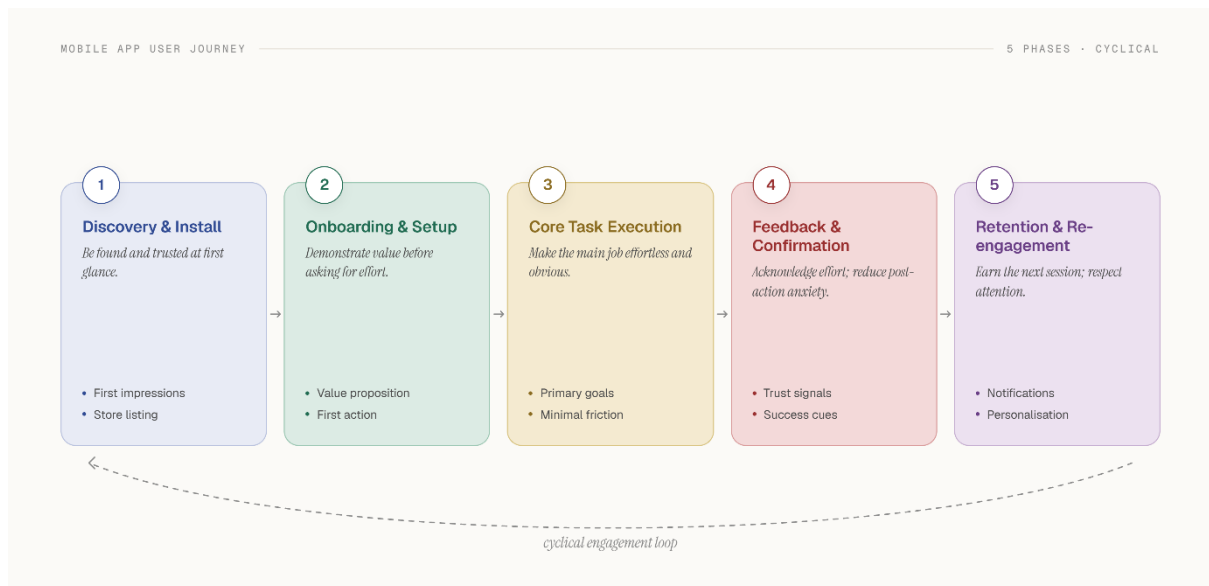
Mobile interactions fundamentally differ from desktop engagement in temporal structure and psychological intent. Where desktop sessions unfold as sustained, uninterrupted stretches of focus, mobile interactions are fragmented, episodic, and driven by immediate contextual need. This shift has profound design implications. Garrett maintains that in such constrained moments, every step must actively advance the user toward their goal there is no space for tangential features or exploratory paths.³ Google's concept of micro-moments captures this episodic reality with precision: these are intent-rich instances in which a person turns to a device to act on a pressing need, moments typically brief and singular in purpose.⁴ What emerges is a design philosophy fundamentally at odds with desktop paradigms. Mobile UX cannot afford the luxury of gradual revelation or feature-rich interfaces. Instead, it must compress intention, interface, and action into the shortest possible arc recognizing that the user has come to accomplish something specific and will abandon the experience instantly if friction interrupts that path.

¹NIELSEN (Jakob) & BUDI (Raluca), op. cit., p. 4.

²NORMAN (Donald A.) (2013), op. cit., p. 11.

³GARRETT (Jesse James), op. cit., p. 21.

⁴GOOGLE, Micro-Moments: Your Guide to Winning the Shift to Mobile, Think with Google, 2015, available at: <https://www.thinkwithgoogle.com/> [accessed: 26 February 2026, 14:55].

Figure 4: Mobile application user journey

Source: Author's elaboration based on Garrett (2011, p. 21); Google (2015); Law et al. (2009, p. 128); Morville (2004).

The journey unfolds across five phases: discovery and installation, onboarding, core task execution, feedback and confirmation, and retention and re-engagement. Law et al. stress that UX evaluation must account for the full scope of this journey.¹ This longitudinal perspective distinguishes rigorous UX assessment from surface-level interface critique. A beautifully designed task-execution screen produces limited value if users never successfully complete onboarding, or if post-task confirmation fails to reinforce confidence in the experience.

1.3.3 Key Challenges in Mobile UX Design

Mobile UX design confronts challenges without desktop counterpart. Mark, Gudith, and Klocke (2008) establish that users shift between activities approximately every three minutes,² This cognitive reality compounds the physical constraint: limited screen real estate demands ruthless content prioritization. Yet shrinking interface density creates a counterintuitive cost. Budi's research demonstrates extremely low tolerance for delays in mobile contexts.³ Speed becomes not an enhancement but a structural requirement. Designers must therefore compress

¹LAW (Effie Lai-Chong) et al., op. cit., p. 128.

²MARK (Gloria), GUDITH (Daniela) & KLOCKE (Ulrich), "The cost of interrupted work: More speed and stress," Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM, New York, 2008, p. 107.

³BUDI (Raluca), "Response Times: The 3 Important Limits," Nielsen Norman Group, 2015, available at: <https://www.nngroup.com/articles/response-times-3-important-limits/> [accessed: 26 February 2026, 14:55].

information, eliminate friction, and optimize performance simultaneously an integration of constraints that fundamentally reshapes how UX is conceived and implemented.

1.3.4 Attention, Engagement, and Measurement

Measuring attention and engagement in mobile user experience is far more nuanced than it might initially appear. Tom Tullis and Bill Albert two of the foremost specialists in usability measurement caution against a widespread interpretive error: treating session duration as a straightforward indicator of positive engagement. A user who lingers on a screen may not be absorbed or satisfied; they may simply be lost. Conversely, a session that ends quickly could reflect effortless goal achievement rather than disinterest. The duration of interaction, taken in isolation, tells us little about its quality.¹ This observation points to a broader methodological imperative. Rigorous evaluation of mobile UX cannot rest on behavioral data alone. Meaningful assessment requires triangulating quantitative metrics with subjective satisfaction measures ratings, perceived effort, emotional response and interpreting both within their proper context of use.

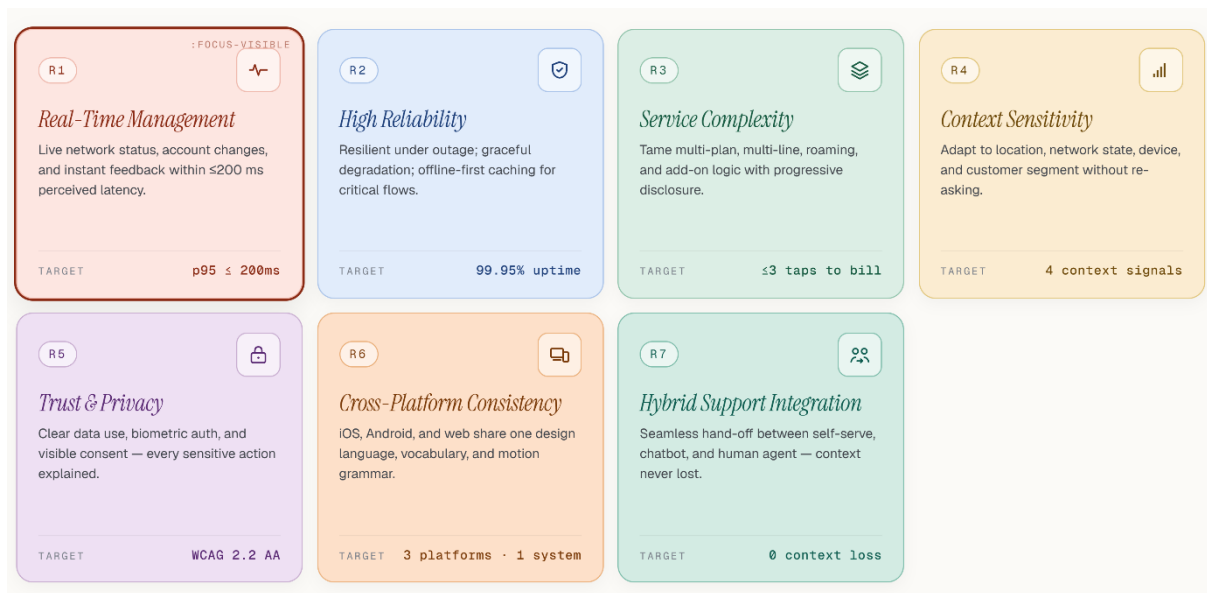
1.4 User Experience in Telecom Mobile Applications

Telecom mobile applications occupy a singular place within the broader digital landscape. Unlike general-purpose tools, they govern services that users consider essential voice, messaging, data plans, billing, and customer support. A failure in any one of these functions carries immediate, tangible consequences. Users therefore approach such applications not in search of delight, but of dependability. This critical dimension shapes the UX challenge in sector-specific ways: reliability is non-negotiable, operational complexity must be absorbed seamlessly by the interface, and regulatory obligations leave their mark on every design decision. Designing for telecom UX, in short, demands a sensibility that goes well beyond aesthetic refinement.

1.4.1 Telecom Service Characteristics Shaping UX

Several characteristics condition UX requirements in telecom applications.

¹TULLIS (Tom) & ALBERT (Bill), *Measuring the User Experience*, 2nd edn, Morgan Kaufmann, Waltham, 2013, p. 64.

Figure 5: UX requirement

Source: Author's elaboration based on Hassenzahl (2010); Nielsen & Budiu (2013); Garrett (2011); Google (2015); ISO 9241-210 (2019); Morville (2004).

Real-time service management means accuracy and responsiveness are non-negotiable baselines when a platform controls something as essential as a user's phone plan, any lag or error is not merely inconvenient but a direct signal that the system cannot be trusted.¹ Service complexity compounds this challenge: plan configurations, billing cycles, and add-on options can quickly overwhelm users who lack the mental scaffolding to navigate them, making careful information architecture not a luxury but a structural necessity.²

1.4.2 Self-Care Journeys and Service-Support Design

When users open a telecom app to manage their account, they arrive with a clear objective and limited patience. Self-care journeys are goal-driven and time-pressured, and good design must honor that. Complex decisions changing a plan, disputing a charge, adjusting an add-on cannot simply be dumped on the user. They require guided pathways: step-by-step explanations that reduce cognitive load and prevent users from feeling stranded at a fork in the road.³ Throughout all of this, trust is the thread that holds the experience together. Users are not simply tracking

¹HASSENZAHN (Marc) (2010), op. cit., p. 40.

²GARRETT (Jesse James), op. cit., p. 21.

³Ibid.p.21.

task completion they are continuously reading the emotional signals the interface sends back to them. Hassenzahl's framework of experience design is particularly instructive here: confirmation feedback, transparent error messaging, and honest status updates at each stage are what transform a transactional interaction into one that feels reliable.¹ And when the self-service flow reaches its limits, the transition to human assistance must feel seamless rather than abrupt. As Følstad and Brandtzæg found in their study of chatbot experiences, users tolerate automation well until it fails without a graceful handoff, at which point frustration spikes sharply.² Hybrid support design, then, is not an afterthought but a core component of any credible self-care architecture.

1.4.3 UX Issues: Friction, Complexity, and Support Quality

Friction in telecom apps rarely announces itself as a single breaking point. It builds gradually through navigation menus that offer too many options at once, forms that demand information the system should already hold, and response times that stretch just long enough to seed doubt. Individually, these are irritants. Collectively, they erode the user's willingness to continue. Garrett's framework is unambiguous on this: user journeys must minimize cognitive load at every step, and where they fail to do so, users don't persist they abandon.³ In telecom contexts, where tasks like modifying a plan or resolving a billing dispute carry inherent complexity, poor flow design doesn't simply slow users down. It stops them entirely; at the precise moment the platform should have delivered.

Support quality adds another layer of failure. When a chatbot returns a generic answer, or an FAQ page acknowledges a problem without resolving it, the damage is never purely practical. Følstad and Brandtzæg's research into chatbot experiences demonstrates that incomplete responses don't just leave tasks unfinished they actively corrode the user's trust in the service as a whole.⁴ A tool that fails to help doesn't leave the user neutral. It leaves them feeling dismissed.

¹HASSENZAHN (Marc) (2010), op. cit., p. 40.

²FOLSTAD (Asbjorn) & BRANDTZAEG (Petter Bae), "Users' experiences with chatbots: findings from a questionnaire study," *Quality and User Experience*, vol. 5, 2020, p. 3.

³GARRETT (Jesse James), op. cit., p. 21.

⁴FOLSTAD (Asbjorn) & BRANDTZAEG (Petter Bae), op. cit., p. 5.

SECTION 2

ARTIFICIAL INTELLIGENCE:

CONCEPTS, ENTERPRISE APPLICATIONS, AND MOBILE SERVICE DIMENSIONS

2.1 Theoretical Foundations and Conceptual Framework of Artificial Intelligence

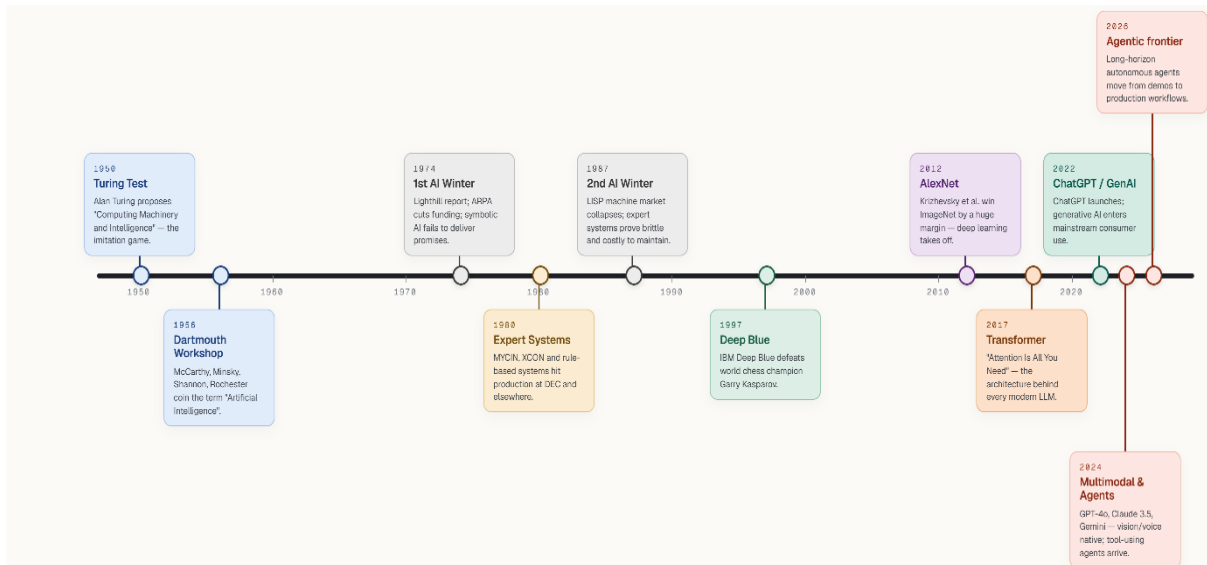
2.1.1 Historical Origins and Conceptual Foundations

The emergence of Artificial Intelligence as a formalized scientific discipline is conventionally dated to the Dartmouth Summer Research Project of 1956.¹ The intellectual antecedents extend further, most notably to Turing's landmark 1950 paper posing the question of whether machines can think and proposing the Imitation Game as a behavioral criterion for machine intelligence.² The field's subsequent trajectory has been characterized by three developmental periods punctuated by two funding contractions known as AI winters: symbolic AI and early optimism (1956–1974); commercially viable expert systems (1980–1987); and the integration of statistical learning, deep learning, and generative AI (1993–present). The Transformer architecture introduced by Vaswani et al. (2017) enabled the Large Language Models that underpin the generative AI era examined in this research.³

¹MCCARTHY (John), MINSKY (Marvin L.), ROCHESTER (Nathaniel) & SHANNON (Claude E.), A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, Dartmouth College, Hanover NH, 1955, p. 1.

²TURING (Alan M.), "Computing Machinery and Intelligence," *Mind*, vol. 59, no. 236, 1950, p. 433-435.

³VASWANI (Ashish) et al., "Attention Is All You Need," *Advances in Neural Information Processing Systems*, vol. 30, 2017, p. 3.

Figure 6: Historical evolution of AI 1950-2026

Source: Author's compilation based on McCarthy et al. (1955, p. 1); Turing (1950, p. 433); Vaswani et al. (2017, p. 3).

2.1.2 Definitions of Artificial Intelligence

No universally accepted definition of AI exists, and the disagreement runs deeper than terminology. Haugeland frames the enterprise at its most ambitious: AI as the effort to make computers think, with human cognition as the reference standard against which machine performance is judged.¹ treating human cognition as the reference standard. deliberately sidestepping the metaphysical question of machine thought. Russell and Norvig (2009) define AI as the study of intelligent agents that maximize chances of success toward specified goals,² Institutionally, UNESCO's 2021 Recommendation extends this further still, offering the most operationally comprehensive definition to date one that positions AI not merely as a technical system but as a sociotechnical phenomenon carrying ethical, societal, and governance implications that reach well beyond engineering.³

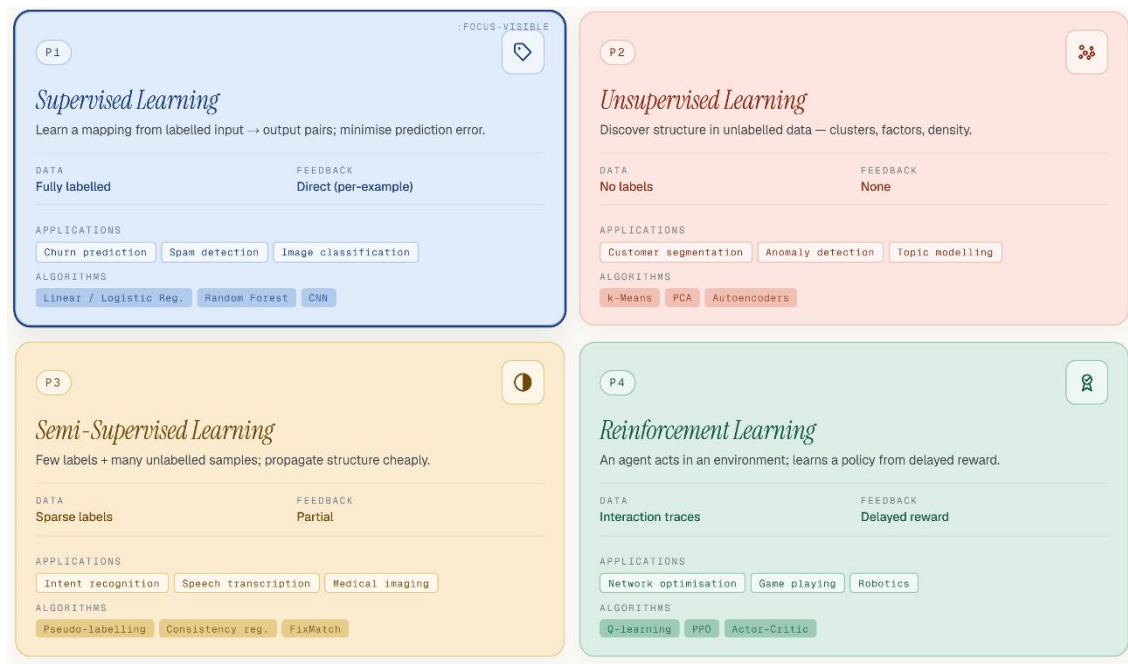
¹HAUGELAND (John), *Artificial Intelligence: The Very Idea*, MIT Press, Cambridge MA, 1985, p. 2.

²RUSSELL (Stuart) & NORVIG (Peter), *Artificial Intelligence: A Modern Approach*, 3rd edn, Pearson, Upper Saddle River NJ, 2009, p. 2-4.

³UNESCO, *Recommendation on the Ethics of Artificial Intelligence*, UNESCO, Paris, 2021, p. 6.

2.1.3 Core AI Technologies

Figure 7: Machine learning paradigms and applications



Source: Author's compilation based on Goodfellow, Bengio & Courville (2016, p. 1).

I. Machine Learning

Machine Learning constitutes the primary operational paradigm of modern AI: statistical algorithms enabling systems to *improve automatically through experience*, generating performance improvements through data exposure rather than explicit programming. ML characterised as learning *representations with multiple levels of abstraction*.¹ Four paradigms structure the landscape: supervised learning (labelled pairs), unsupervised learning (pattern discovery), semi-supervised learning (limited labels), and reinforcement learning (trial-and-error interaction).

II. Deep Learning

Deep learning represents a qualitative leap rather than an incremental refinement. By stacking multiple layers of neural networks, it enables machines to learn hierarchical representations of data moving from raw input to increasingly abstract patterns without being told what to look

¹GOODFELLOW (Ian), BENGIO (Yoshua) & COURVILLE (Aaron), Deep Learning, MIT Press, Cambridge MA, 2016, p. 1-2.

for. The deep architectures allow machines to discover needed representations from raw data.¹ Two architectural families have proven directly consequential for the AI landscape this thesis examines. Convolutional Neural Networks brought deep learning to grid-structured data images, audio, spatial patterns and demonstrated that hierarchical feature extraction could match and exceed human performance on perceptual tasks, the Transformer architecture, constituting the breakthrough enabling contemporary LLM chatbots.²

III. Natural Language Processing

Natural Language Processing is the subfield of AI that takes on one of computing's most demanding challenges: teaching machines to understand and generate human language. At its core, as IBM defines it, NLP bridges the gap between the structured logic machines process and the ambiguous, context-dependent way humans actually communicate drawing on computational linguistics, statistical modelling, and deep learning to do so.³ For chatbot systems, four tasks form the operational backbone: intent classification identifies what the user is trying to accomplish; named entity recognition extracts the meaningful elements from their request; sentiment analysis reads the emotional register of the interaction; and dialogue management holds the conversation together across turns, maintaining context and deciding what comes next.

2.1.4 AI Typologies: Narrow AI, General AI, and Superintelligence

AI research and strategic discourse employ a capability typology classifying systems according to the breadth and depth of cognitive functioning relative to human intelligence. This typology is not merely descriptive but analytically consequential: it conditions what benefits and what risks are associated with any given AI deployment, and it establishes the theoretical ceiling within which practical AI systems must be understood. the definitive clarification: *Narrow AI is the only type of AI that exists today*.⁴ Every AI capability of chatbot is structurally incapable of generalizing beyond its training distribution. Bostrom (2014) defines superintelligence as

¹LECUN (Yann), BENGIO (Yoshua) & HINTON (Geoffrey), "Deep learning," *Nature*, vol. 521, no. 7553, 2015, p. 436.

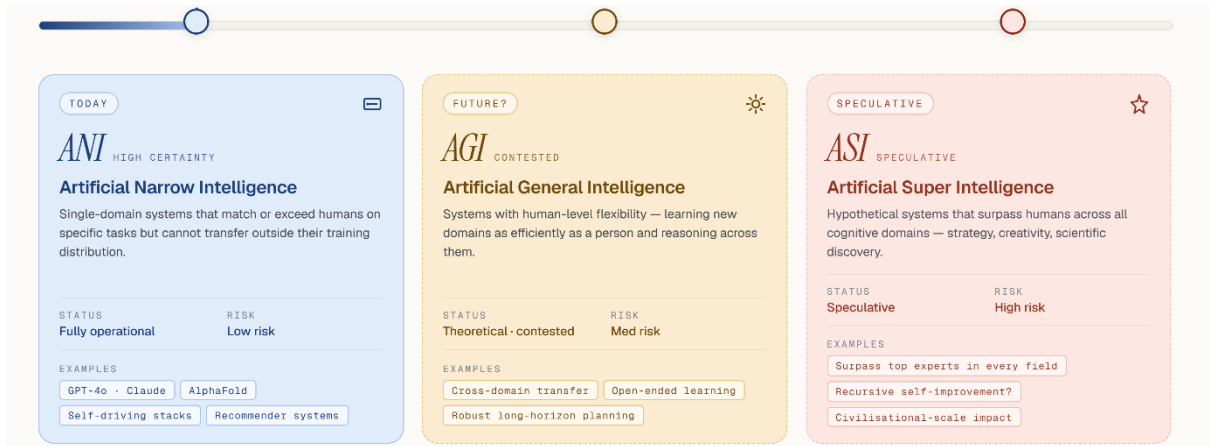
²VASWANI (Ashish) et al., op. cit., p. 3-4.

³IBM, "What Is NLP (Natural Language Processing)?," available at: <https://www.ibm.com/topics/natural-language-processing> [accessed: 15 March 2025, 10:30].

⁴IBM, "Understanding the Different Types of Artificial Intelligence," available at: <https://www.ibm.com/think> [accessed: 15 March 2025, 11:00].

*any intellect that greatly exceeds human cognitive performance in virtually all domains, a capability horizon that remains entirely theoretical.*¹

Figure 8: AI capability



Source: Author's elaboration based on IBM (2023); Bostrom (2014, p. 22).

2.1.5 AI in the Organisational Context

Three forces converged to move AI from the research laboratory into the organizational mainstream. Data abundance gave machine learning systems the raw training material they needed generated in vast quantities through e-commerce, social media, IoT networks, and mobile usage. Plummeting processing costs, driven by GPU acceleration and cloud infrastructure, made deploying large AI models economically viable for commercial organizations. And the maturation of deep learning algorithms above all the Transformer architecture's breakthrough on language tasks produced systems capable of performing in domains that had previously required exclusively human expertise. None of these drivers alone would have been sufficient. Together, they made the current AI adoption wave inevitable. the most influential framework: a three-tier cognitive technology taxonomy.² Cognitive automation handles rule-based task execution the displacement of repetitive processes by intelligent systems. Cognitive insight turns data into foresight through pattern detection and prediction.³ Cognitive engagement, the tier most directly relevant to this research, covers real-time

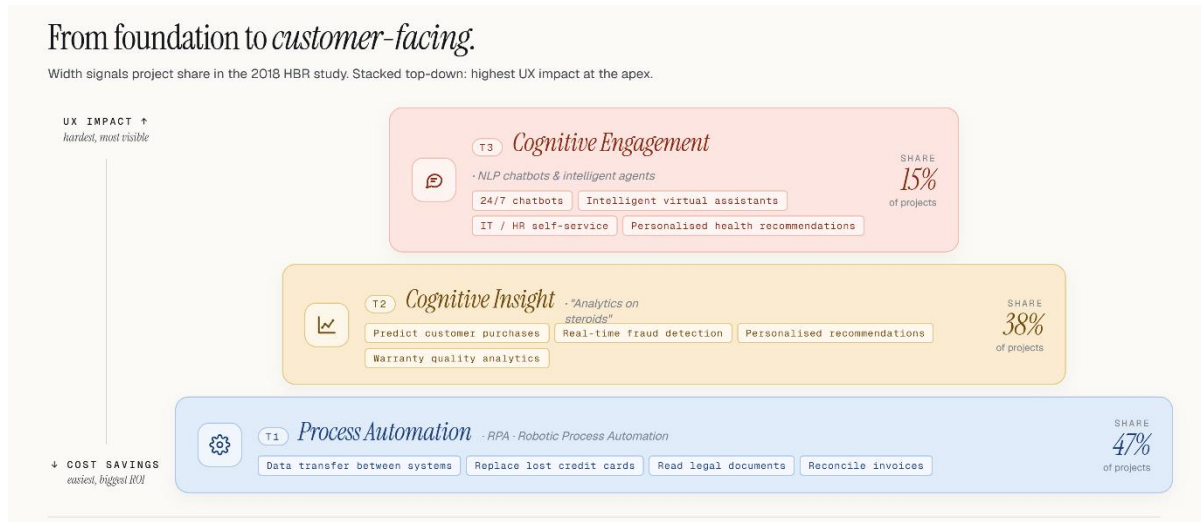
¹BOSTROM (Nick), *Superintelligence: Paths, Dangers, Strategies*, Oxford University Press, Oxford, 2014, p. 22.

²DAVENPORT (Thomas H.) & RONANKI (Rajeev), "Artificial Intelligence for the Real World," *Harvard Business Review*, vol. 96, no. 1, 2018, p. 109.

³*Ibid.*, p. 112.

interaction with humans through natural language interfaces the domain in which AI chatbots operate, and the domain in which the quality of the user experience is most directly at stake.

Figure 9: Three-tier cognitive technology framework



Source: Author's elaboration based on Davenport & Ronanki (2018, pp. 109–112).

NVIDIA's 2024 State of AI in Telecom report reveals that while 89% of telecom companies are already using AI, only 26% have achieved full operational integration.¹ This gap between surface-level adoption and deep operational embedding reflects a structural challenge: deploying an AI tool and genuinely transforming service workflows around it are two fundamentally different undertakings. For telecom operators, closing that gap requires not just technological investment but organizational readiness the processes, skills, and governance frameworks that allow AI to deliver on its promise at scale.

2.2 AI Applications in Firms and Enterprise Contexts

2.2.1 AI for Operations and Efficiency

At the operational tier of enterprise AI sits a category of systems whose purpose is straightforward but whose impact is substantial: automating, accelerating, and optimising processes that previously consumed significant human time and attention. Brynjolfsson and McAfee demonstrate that AI-driven automation generates measurable productivity gains precisely by eliminating the constraints human labour cannot escape processing speed limits,

¹NVIDIA, State of AI in Telecom: Annual Report 2024, NVIDIA Corporation, Santa Clara CA, 2024, p. 4.

attention fatigue, and the hard boundaries of shift-based availability.¹ In telecom network infrastructure, where an unplanned outage does not simply disrupt operations but immediately degrades user experience in ways that are both visible and lasting, these efficiency gains translate directly into service quality outcomes.

Fraud detection represents another high-value domain. Anomaly detection algorithms particularly hybrid approaches combining gradient boosted trees with deep autoencoders identify suspicious transaction patterns in real time with accuracy that rule-based systems cannot match. Gupta et al. confirm that these hybrid machine learning approaches significantly outperform traditional rule-based fraud detection across multiple performance dimensions.² In telecom organisations specifically, the operational AI tier spans SIM activation workflows, billing adjustment processing, complaint ticket routing, invoice extraction, and contract handling functions that previously absorbed substantial agent capacity without producing any improvement visible to the end user. Making them faster and more accurate frees human expertise for the interactions where it actually matters.

2.2.2 AI for Decision-Making and Analytics

The analytics tier of enterprise AI transforms an organisation's capacity to generate actionable insight from data moving from retrospective reporting through real-time monitoring to prospective intelligence. the evolution from traditional Business Intelligence toward AI-powered predictive and prescriptive systems, tracing four maturity levels that mark an organisation's analytical progression: descriptive analytics establishes what happened, diagnostic analytics explains why, predictive analytics anticipates what is likely to happen next, and prescriptive analytics recommends what should be done about it.³

¹BRYNJOLFSSON (Erik) & MCAFEE (Andrew), "The Business of Artificial Intelligence," Harvard Business Review Digital Articles, 2017, p. 5.

²Gupta, S., et al. (2022). A Hybrid Machine Learning Approach for Credit Card Fraud Detection. *Journal of Information Technology Management*, 13(3), pages 1-13.

³CHEN (Hsinchun), CHIANG (Roger H.L.) & STOREY (Veda C.), "Business intelligence and analytics: From big data to big impact," MIS Quarterly, vol. 36, no. 4, 2019, p. 1168.

2.2.3 AI for Customer Relationship and Service Transformation

Of all the tiers of enterprise AI, the customer engagement layer is the most visible and the most consequential for how users actually experience an organisation. It is here that AI stops being a back-office efficiency tool and becomes something users directly perceive, evaluate, and form opinions about. Huang and Rust offer a useful framework for understanding this layer's range: three capability levels that move from the mechanical to the deeply human. Mechanical AI handles task automation the straightforward execution of routine requests. Thinking AI introduces analytical personalisation, adapting responses based on data and context. Feeling AI reaches furthest, aspiring to empathic responsiveness that reads and reflects the emotional register of the interaction.¹ The AI-powered service automation reduces handling time by 40 to 70% for standard requests. with leading telecom deployments achieving contact centre volume reductions of up to 68%.² Sentiment analysis applied to chat transcripts, social media mentions, call recordings, and survey responses generates continuous, real-time intelligence about customer satisfaction patterns, replacing the periodic customer satisfaction survey with a continuous intelligence stream that feeds service improvement processes.

2.3 AI in Mobile Applications

Mobile applications represent the primary site at which AI's organisational capabilities and individual users' experiential expectations intersect in the most direct and consequential way. The smartphone has become the dominant interface through which individuals access services, conduct transactions, manage relationships, and consume information, making mobile applications the strategic frontier of AI-driven service differentiation. Eurostat (2024) documents that mobile devices account for over 60% of digital service interactions.³ and mobile application usage has displaced web browsing as the default channel for accessing organisational services across most demographic groups. For organisations, this concentration of user activity on a single, handheld interface makes the mobile application not just a product feature but the strategic frontier of AI-driven service differentiation the place where the gap

¹HUANG (Ming-Hui) & RUST (Roland T.), "Artificial intelligence in service," *Journal of Service Research*, vol. 21, no. 2, 2018, p. 158.

²WIRTZ (Jochen), KUNZ (Werner H.) & PALUCH (Stefanie), "The service revolution, intelligent automation and service robots," *European Business Review*, 2021, p. 41.

³EUROSTAT, "Digitalisation in Europe : 2024 edition," European Commission, Luxembourg, 2024, p. 22.

between a good experience and a forgettable one is most immediately apparent, and most consequential.

2.3.1 Where AI Appears in the Mobile User Journey

AI interventions are distributed across the full arc of the mobile user journey, from application discovery through active service use to post-interaction analytics. Rather than constituting isolated feature additions, AI capabilities collectively transform the experiential architecture of the journey by eliminating friction at multiple stages simultaneously, creating a compound UX effect that exceeds the sum of individual AI improvements. Venkatesh, Thong, and Xu (2012) establish in UTAUT2 that facilitating conditions significantly moderate the intention-use relationship.¹

2.3.2 AI-Enabled Personalisation and Recommendation

Personalisation constitutes the most pervasive and commercially consequential form of AI in mobile applications: the capacity of a system to continuously adapt its content, interface configuration, and service outputs to the specific characteristics, preferences, and behavioural history of each individual user. Modern approaches combine content-based, collaborative, and hybrid filtering to build increasingly accurate models of individual preference models that improve with every interaction. Pathak et al. demonstrate that LLM-powered personalisation goes further still, producing a genuine sense of resonance in users that elevates post-interaction loyalty in measurable ways.² Yet the ethical dimension is equally significant and cannot be treated as secondary. Goodman and Flaxman caution that opaque recommendation systems can produce discriminatory outcomes surfacing systematically different content, offers, or service quality to different user groups in ways that are neither visible nor easily contestable.³ Personalisation, in other words, is powerful precisely because it is invisible which is exactly what makes its governance so important.

2.3.3 AI-Enabled Search, Automation, and Intelligent Support

¹VENKATESH (Viswanath), THONG (James Y.L.) & XU (Xin), "Consumer acceptance and use of information technology: Extending UTAUT2," MIS Quarterly, vol. 36, no. 1, 2012, p. 161.

²PATHAK (Kanika) et al., "Impact of Gen-AI chatbots on consumer services and future research directions," Journal of Retailing and Consumer Services, vol. 82, 2025, p. 4.

³GOODMAN (Bryce) & FLAXMAN (Seth), "European Union regulations on algorithmic decision-making and a right to explanation," AI Magazine, vol. 38, no. 3, 2017, p. 52.

Semantic search and intent understanding have fundamentally reordered what in-application search can accomplish. Where traditional keyword-based systems require users to mirror the application's own terminology, NLP-powered search operates at the level of meaning recognizing synonyms, paraphrases, and implicit intent without demanding lexical precision from the user.

Intelligent autocomplete and predictive input extend this logic to the interaction layer itself, anticipating the next action, form entry, or navigation step before the user has completed it. The UX gain is disproportionately significant on mobile, where touchscreen constraints make every eliminated input step a tangible reduction in cognitive and physical load. AI agents push this principle further still, moving from prediction to full task execution: activating service options, scheduling payments, resolving billing queries all without requiring the user to navigate explicit menus. Roder , whose work maps practical AI deployment across enterprise contexts, characterizes the most advanced expression of this capability as ambient intelligence: *AI operating as a background service layer*.¹

Proactive notifications mark AI's transition from reactive to anticipatory service design. Rather than dispatching generic alerts on fixed schedules, AI-driven systems generate individually timed messages calibrated to each user's consumption patterns, behavioural rhythms, and account state. Khrais (2020) confirms that the engagement advantage of personalized notifications stems not from content alone, but from timing models that identify the precise moment a user is most receptive achieve results that no fixed-schedule system can replicate.²

2.3.4 Data Foundations in Mobile Environments

The quality of AI outputs in mobile applications is directly dependent on the richness and recency of the underlying data. Interaction data every tap, scroll, search, session duration, and task abandonment generates the behavioural signals from which machine learning models infer preferences and personalise subsequent experiences, reaching thousands of events per user per month in actively used applications. Contextual data extends this further: location, time of day, connectivity status, and device state allow AI systems to move beyond static preference profiles toward dynamic, situation-aware personalisation. ContextSDK documents engagement gains

¹RODER (Stéphane), Guide pratique de l'intelligence artificielle en entreprise, Eyrolles, Paris, 2019, p. 118.

²KHRAIS (Laith Tawfik), "Role of artificial intelligence in shaping consumer demand in e-commerce," Future Internet, vol. 12, no. 12, 2020, p. 8.

of 35 to 45% when real-time contextual signals are integrated, enabling models to determine not only what users prefer, but when and where those preferences are most actionable.¹ Historical service data account records, billing patterns, support logs completes the picture by providing the longitudinal depth that predictive models require for reliable individual-level outputs.

Yet this data richness carries governance obligations that directly condition AI performance. GDPR-mandated deletion rights create temporal gaps in behavioural histories, while new users present a structural cold-start problem whereby personalisation algorithms systematically underperform in the absence of sufficient interaction history. the privacy-utility trade-off as a central design challenge² one that is particularly acute in the telecom context, where operators hold comprehensive behavioural data capable of surfacing sensitive inferences about users' social networks, economic circumstances, and daily routines. Responsible operators must navigate this tension through explicit, proactive governance frameworks rather than treating it as a compliance formality.

2.4 AI in Telecom Mobile Applications and the 5G Context

The telecommunications sector occupies a structurally privileged position in the AI deployment landscape. Unlike most industries, which engage with AI along a single axis, telecom operators interact with it on three simultaneous fronts: as an environment in which AI is deployed, as an operational user of AI for internal management, and as a distributor of AI capabilities through the mobile applications delivered to end users. This triple role generates compounded strategic interest and places telecom operators among the most AI-intensive organisations globally.

Historically, AI integration in the sector evolved through successive waves from expert systems for billing and tariff optimization in the 1990s, through customer segmentation and network planning analytics in the 2000s, to machine learning models for churn prevention, fraud detection, and network optimization in the 2010s. The current wave, defined by generative AI and NLP-powered conversational interfaces, is the one most directly relevant to the user experience examined in this research. GSMA Intelligence confirms that AI has become the

¹CONTEXTSDK, "Mobile Context Data and Personalization," available at: <https://contextsdk.com> [accessed: 20 March 2025, 14:00].

²RAWASSIZADEH (Reza) et al., "Manifestation of virtual assistants and robots into daily life," CCF Transactions on Pervasive Computing and Interaction, vol. 1, no. 2, 2019, p. 168.

primary strategic investment priority for telecom operators globally.¹ a designation that reflects not only the transformative potential of AI deployment, but the competitive pressure of an industry where failing to exploit AI capabilities risks ceding market share to rivals who will.

2.4.1 AI Use Cases in Telecom Service Ecosystems

The GSMA (2024), the leading international body representing mobile network operators worldwide, identifies AI adoption in the telecom sector as concentrated across six strategic domains.²

Table 1: Principal AI Use Cases in the Telecommunications Sector

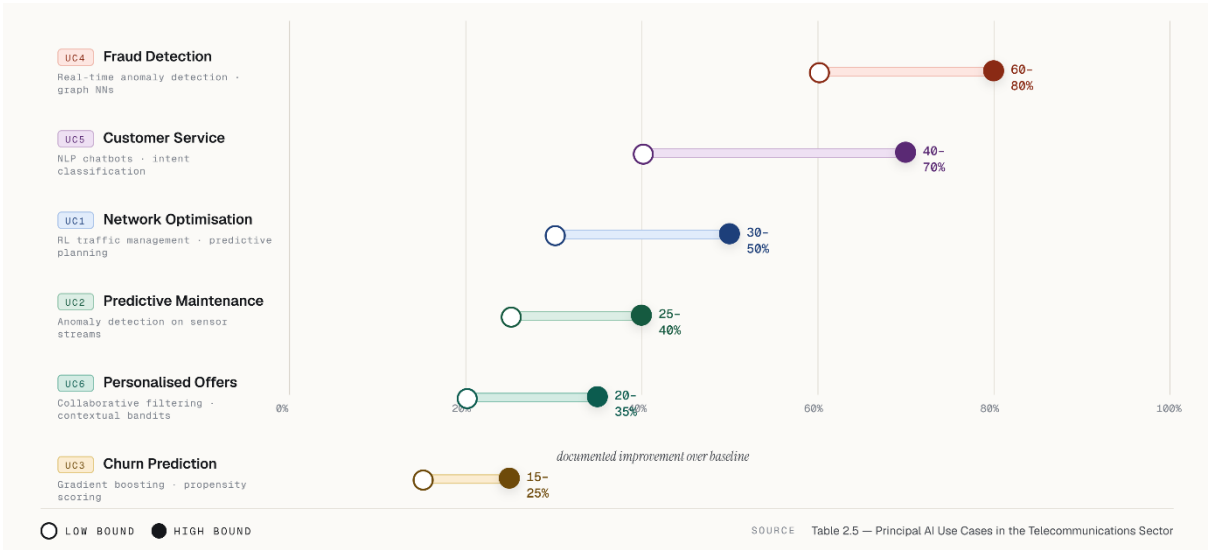
AI Use Case	Technology Applied	Documented Benefit
Network Optimisation	RL-based traffic management; predictive planning	30–50% congestion reduction; 20% CAPEX gain
Predictive Maintenance	Anomaly detection on sensor streams	25–40% reduction in unplanned outages
Churn Prediction	Gradient boosting; propensity scoring	15–25% retention rate improvement
Fraud Detection	Real-time anomaly detection; graph NNs	60–80% fraud revenue loss reduction
Customer Service	NLP chatbots; intent classification	40–70% tier-1 volume reduction
Personalised Offers	Collaborative filtering; contextual bandits	20–35% offer acceptance improvement

Source: Author’s compilation based on GSMA (2024, pp. 18–22); NVIDIA (2024, p. 4); Wirtz, Kunz & Paluch (2021, p. 41).

¹GSMA INTELLIGENCE, The Mobile Economy 2024, GSM Association, London, 2024, p. 3.

²GSMA, AI in Telecom: Use Cases and Value Creation, GSM Association Intelligence Report, 2024, p. 18.

Figure 10: AI use cases



Source: Author’s elaboration based on NVIDIA (2024, p. 4); GSMA (2024, pp. 18–22).

NVIDIA (2024) confirms that 89% of telecom companies globally use AI, while only 26% report full integration.¹ with the distribution of outcomes across operators reflecting the quality variation in NLP capabilities, data richness, and implementation governance that the NVIDIA maturity gap data documents at the industry level.

2.4.2 5G, Service Performance, and AI-Driven Experience

The transition to 5G represents the most significant infrastructure shift in mobile telecommunications since 4G/LTE, with implications for AI-powered applications that are both technical and experiential. Where 4G set a performance floor, 5G raises it to a level where inconsistency and latency become more perceptible to users not less. Meeting these elevated expectations consistently is a task only AI-powered systems can fulfil at scale. The Ericsson Mobility Report (2024) organises 5G's AI relevance around three capability dimensions.²

Enhanced Mobile Broadband (eMBB) provides peak download speeds of 1 to 10 Gbps against 100 to 300 Mbps on 4G LTE,³ making cloud-based AI inference viable for data-intensive interactions such as real-time video analysis and AR overlays.

¹NVIDIA, op. cit., p. 4-6.
²ERICSSON, *Ericsson Mobility Report, June 2024*, Ericsson AB, Stockholm, 2024, p. 8.
³*Ibid.*, p. 10.

Ultra-Reliable Low-Latency Communication (URLLC brings latency below one millisecond compared to 20 to 50 milliseconds on 4G enabling instant chatbot responses, live sentiment analysis, and sub-millisecond fraud detection, improvements that are particularly consequential given that response speed is a primary determinant of conversational AI satisfaction.

Massive Machine-Type Communication (mMTC) supports up to 1 million connected devices per square kilometre, enabling the IoT sensor ecosystem that generates the contextual data streams on which mobile AI personalisation increasingly depends.

Huawei's 5G-Advanced White Paper extends this framework to the 5G-Advanced paradigm, characterised as the intermediate step between 5G and 6G, which adds Network AI as a native service: AI capabilities embedded directly into the network infrastructure rather than deployed as application-layer additions.¹ This architectural evolution means that future telecom mobile applications will have access to network-embedded AI capabilities, including predictive resource allocation, network-native natural language processing, and distributed edge AI, that are not yet available in current 4G-dominated deployment environments.

Ookla's Q4 2024 Global Index documents that Algeria's average 5G download speed reached 287 Mbps in commercial deployments,² confirming the accessibility of basic 5G capabilities in the research context while acknowledging that the full performance envelope of advanced 5G features remains under development in the Algerian market.

2.5 Chatbots and Virtual Assistants as AI-Based Service Support

Among the various AI systems deployed in mobile service environments, chatbots and virtual assistants occupy the most direct and consequential position in the AI-user interface. Unlike recommendation algorithms or predictive analytics which operate invisibly behind the service layer the chatbot presents a visible, interactive, and immediately assessable agent whose performance is experienced and judged by users in real time. Adamopoulou and Moussiades characterise it as the frontline ambassador of an organisation's AI capabilities,³ a framing that captures both the strategic importance and the reputational risk of chatbot deployment: every

¹HUAWEI, **5G-Advanced: The Path to 6G**, Huawei Technologies White Paper, 2023, pp. 6 to 9.

²OOKLA, *Speedtest Global Index Q4 2024*, Ookla LLC, 2024.

³ADAMOPOULOU (Eleni) & MOUSSIADES (Lefteris), "An overview of chatbot technology," *Proceedings of AIAI 2020, IFIP Advances in Information and Communication Technology*, vol. 584, Springer, 2020, pp. 373 to 383.

interaction that resolves a billing dispute accurately and empathetically converts a potential grievance into a positive brand encounter, while every failure a misunderstood query, a refused escalation erodes trust in ways that extend well beyond the individual exchange. Understanding chatbot systems in depth, encompassing their architecture, quality determinants, UX impacts, failure modes, and trust repair mechanisms, is therefore central to the theoretical framework of this research.

2.5.1 Roles and Value in Mobile Applications

AI chatbots serve five distinct functional roles within mobile service architectures, each generating value through different mechanisms and carrying different quality requirements. First-line service resolution is the most operationally significant: handling high-volume, standardised tier-1 requests account balance queries, billing explanations, service activation, complaint registration at zero wait time and zero staffing cost. Continuous availability extends this logic beyond business hours, transforming service access from time-constrained to always-on. Personalised service guidance leverages individual account data and usage history to deliver contextually relevant responses, distinguishing AI chatbots from static FAQ systems in ways users directly perceive. Proactive notification delivery extends the chatbot's role from reactive resolution to anticipatory service management, generating alerts based on real-time account and network monitoring. Finally, every chatbot interaction constitutes simultaneously a service delivery event and a data collection event, feeding transcripts and behavioural signals into continuous service improvement processes.

The operational case for chatbot deployment is well documented. Wang, Lin, and Shao (2022) demonstrate that AI chatbots create a form of organizational agility the capacity to absorb demand peaks instantly that human-only service systems cannot replicate at scale.¹ Wirtz, Kunz, and Paluch confirm that leading telecom chatbot deployments achieve total contact centre volume reductions of up to 68% for standard queries,² a figure with direct commercial implications: operators that successfully deflect the majority of tier-1 interactions to AI can

¹WANG (Xinwei), LIN (Xiaolin) & SHAO (Bingjia), "How does artificial intelligence create business agility? Evidence from China's manufacturing sector," *International Journal of Information Management*, vol. 66, 2022, pp. 1 to 14.

²WIRTZ (Jochen), KUNZ (Werner H.) & PALUCH (Stefanie), "The service revolution, intelligent automation and service robots," *European Business Review*, 2021, pp. 43 to 44.

redeploy human agent capacity toward the complex, emotionally sensitive cases where human judgement generates the highest value and cannot be replaced.

2.5.2 Types and Integration Modes

Adamopoulou and Moussiades establish a chatbot taxonomy organised by architecture, purpose, and integration mode that structures the strategic choices available to telecom operators.¹ Rule-based chatbots, built on pre-defined decision trees and keyword matching, offer high reliability and fully predictable behaviour within their programmed scope but become brittle the moment users express needs outside anticipated formulations. Machine learning-powered retrieval chatbots apply NLP intent classification to select responses from curated knowledge bases, achieving higher accuracy on known intents while still failing on out-of-scope queries and requiring continuous maintenance. Generative chatbots, powered by large language models, produce open-domain conversational responses without a fixed script delivering natural, adaptive dialogue at the cost of hallucination risk, higher computational overhead, and the governance challenge of controlling outputs that cannot be pre-approved. Hybrid architectures, combining rule-based handling of core service flows with large language model capability for edge cases, achieve the most practical balance between reliability and flexibility, though at the price of architectural complexity and sophisticated intent routing logic.

Table 2: Chatbot Architecture Typology and Comparative Analysis

Chatbot Type	Architecture	Strengths	Limitations
Rule-Based	Pre-defined decision trees; keyword matching	High reliability within programmed scope; fully predictable	Zero flexibility outside rules; brittle to unexpected input; high maintenance
ML-Powered Retrieval	NLP intent classification; knowledge base response selection	High accuracy on known intents; explainable retrieval logic	Fails on out-of-scope intents; knowledge base maintenance required

¹ADAMOPOULOU (Eleni) & MOUSSIADES (Lefteris), *op. cit.*, pp. 374 to 376.

Generative (LLM-Based)	Large language model; open-domain generative responses	Open-domain capability; natural adaptive conversation	Hallucination risk; higher computational cost; governance challenge
Hybrid	Rule-based core flows plus LLM for open intents	Combines reliability and flexibility	Architectural complexity; sophisticated routing logic required

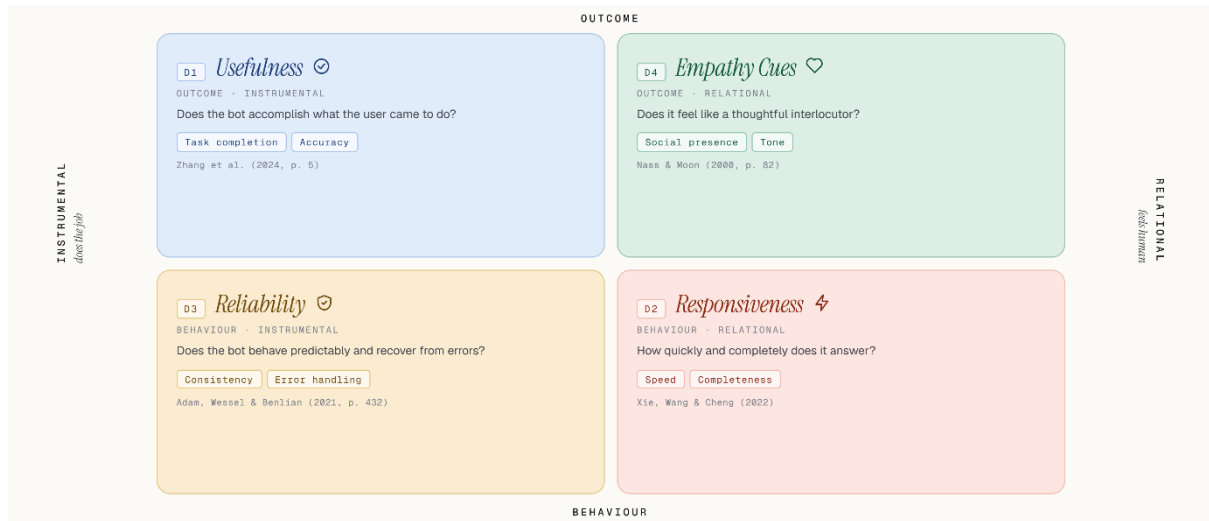
Source: Author's compilation based on Adamopoulou & Moussiades (2020, pp. 374 to 376); Gnewuch et al. (2023, pp. 942 to 946).

Gnewuch et al. establish a finding with direct implications for chatbot design in the telecom context: users informed proactively before the interaction begins that they are engaging with an AI report significantly higher satisfaction than those who discover its nature mid-conversation or are never informed at all.¹ Proactive disclosure functions as an expectation calibration mechanism: users who enter with accurate AI-level expectations evaluate performance more favorably than those whose mental model was calibrated to human-level interaction and who experience a negative recalibration upon discovery. This finding carries a direct regulatory dimension the EU AI Act classifies telecom chatbots under its limited risk category, which mandates precisely this form of proactive disclosure as a transparency obligation.

2.5.3 Chatbot Quality Factors:

Chatbot quality is not a single dimension but a composite of interdependent factors, each capable of independently determining whether an interaction succeeds or fails in the user's experience. The framework elaborated here draws on four dimensions established in the research literature.

¹GNEWUCH (Ulrich) et al., "More than a bot? Unveiling the need for human agent involvement in AI-based customer service systems," *Information Systems Research*, vol. 35, n°3, 2023, pp. 942 to 946.

Figure 11: Chatbot service quality dimensions

Source: Author's elaboration based on Adam, Wessel & Benlian (2021, p. 432); Xie, Wang & Cheng (2022); Zhang et al. (2024, p. 5); Nass & Moon (2000, p. 82).

I. Usefulness: Task Completion Quality

The most fundamental quality dimension is the chatbot's capacity to resolve the user's service request. Adam, Wessel, and Benlian (2021) demonstrate through experimental methodology that task completion rate is the primary determinant of satisfaction and continued use intention across service contexts.¹ Usefulness encompasses four components: accuracy of information, completeness of the service action performed, relevance to the user's specific account situation, and appropriateness of register given the user's emotional context. Each can be independently degraded by distinct AI performance failures and degradation in any single component is sufficient to produce a failed interaction, even when the remaining three perform adequately.

II. Responsiveness: Speed and Completeness

Responsiveness encompasses both latency the interval between user input and chatbot reply and completeness, meaning the degree to which a single response addresses the full query without requiring clarification exchanges. In mobile contexts where users are frequently time-constrained and operating under divided attention, response speed carries disproportionate

¹ADAM (Marc), WESSEL (Michael) & BENLIAN (Alexander), "AI-based chatbots in customer service and their effects on user compliance," *Electronic Markets*, vol. 31, 2021, pp. 432 to 436.

weight. Xie, Wang, and Cheng's meta-analysis confirms that perceived response quality, combining speed and completeness, is the strongest single predictor of chatbot satisfaction across diverse service contexts.¹ This finding is particularly consequential in the 5G environment: URLLC latency below one millisecond enables chatbot response timing that approaches human conversational rhythm, removing one of the most persistent sources of negative differentiation between AI and human service quality.

III. Reliability: Consistency of Accurate Responses

Chatbot reliability refers to the consistency of accurate responses across repeated and varied user inputs over time. Zhang et al. establish a critical asymmetry in how users evaluate chatbot reliability compared with human agent reliability: users apply significantly higher reliability standards to AI systems than to human agents, and service failures are experienced as more disturbing and more trust-damaging when attributed to a supposedly intelligent system than when attributed to human fallibility.² A single chatbot misunderstanding leads users to infer global system unreliability a generalisation that a single human error, attributed to individual variability rather than systemic inadequacy, does not trigger. The design implication is clear: chatbot systems must invest more heavily in graceful handling of uncertain inputs, explicit acknowledgment of knowledge boundaries, and proactive escalation offers than human agent training requires, precisely because the recovery cost of AI failure is higher.

IV. Empathy Cues and Social Presence

Nass and Moon established the CASA paradigm Computers Are Social Actors demonstrating that users systematically extend social attributions to conversational AI, treating it as a social actor governed by social norms even when fully aware it is not human.³ This attribution activates reciprocity norms, politeness conventions, and trust formation mechanisms ordinarily reserved for interpersonal interaction. Chatbots that incorporate empathy cues acknowledgment of frustration, contextually appropriate apology, consistent persona expression achieves significantly higher satisfaction than functionally equivalent systems with purely transactional response styles.

¹XIE (Chennan), WANG (Yujia) & CHENG (Yi), "Does artificial intelligence satisfy you? A meta-analysis of user technology satisfaction and acceptance," *International Journal of Human-Computer Interaction*, 2022.

²ZHANG (Jinwei) et al., "The influence of service failures on user reusage intention in AI chatbot: From a perspective of stress-coping theory," *Electronic Commerce Research and Applications*, vol. 67, 2024, pp. 5 to 7.

³NASS (Clifford) & MOON (Young-Me), "Machines and mindlessness: Social responses to computers," *Journal of Social Issues*, vol. 56, n°1, 2000, pp. 82 to 84.

Liu et al. confirm that chatbot anthropomorphism positively moderates reuse intention through parasocial relationship formation, with the effect most pronounced in high-stakes interactions involving complaints, billing disputes, and service outages.¹

Alagarsamy and Mehroliia refine this further by distinguishing cognitive trust, derived from competence-based assessments of accuracy and reliability, from affective trust, derived from perceived warmth and genuine intent to help establishing that both are necessary for committed user loyalty and each requires distinct design investment, establishing that both trust components are necessary for committed user loyalty and that each requires distinct design investments.² Pathak et al. extend these findings to the generative AI context, demonstrating that LLM-powered chatbots capable of contextually nuanced empathic responses generate an awe response that significantly elevates post-interaction loyalty intent and word-of-mouth recommendation likelihood.³

2.5.4 Escalation and Human Handoff

Human escalation pathways the mechanisms through which chatbot interactions are transferred to human agents when the AI reaches its capability boundaries are among the most consequential and most frequently underestimated elements of AI-powered service design. Every escalation event is simultaneously a chatbot failure, which has already generated negative satisfaction effects, and a human service opportunity whose quality determines whether the overall interaction is ultimately remembered as a frustrating breakdown or a successful recovery. De Keyser et al. establish that the quality of the human-AI handoff is an independent UX dimension whose effects on overall satisfaction cannot be explained either by the chatbot performance preceding it or the human agent performance following it.⁴ Poorly designed transitions can transform a satisfactory chatbot interaction into a negative experience and can undermine high-quality human agent performance by creating the relational conditions of frustration and distrust within which that performance is inevitably evaluated.

¹LIU (Wenxin) et al., "How does the anthropomorphism of AI chatbots facilitate users' reuse intention? The moderating role of negative emotions," *Technological Forecasting and Social Change*, vol. 203, 2024, pp. 4 to 6.

²ALAGARSAMY (Subburaj) & MEHROLIA (Sangeeta), "Exploring chatbot trust: Antecedents and behavioural outcomes," *Heliyon*, vol. 9, n°5, 2024, pp. 4 to 7.

³PATHAK (Kanika) et al., "Impact of Gen-AI chatbots on consumer services and future research directions," *Journal of Retailing and Consumer Services*, vol. 82, 2025, pp. 4 to 7.

⁴DE KEYSER (Anja) et al., "Frontline service technology infusion: Conceptual archetypes and future research directions," *Journal of Service Management*, vol. 30, n°1, 2019, pp. 165 to 168.

Handoff quality is determined by four independent components: context transfer, meaning whether the human agent receives the full conversation history without requiring users to repeat themselves; wait time management, meaning how queue time is communicated; channel continuity, meaning whether escalation preserves the mobile interface or forces a channel switch; and emotional recalibration, meaning whether the agent's opening acknowledges the user's potential frustration. transparency about escalation proactively informing users they are being transferred and explaining why significantly improves overall satisfaction compared to silent or defensive escalation.¹ users experiencing smooth, context-informed escalations after chatbot failures exhibit retention probabilities comparable to those who never encountered a failure at all,² establishing that effective escalation design can fully offset the loyalty damage of AI service failures when executed with sufficient care.

2.5.5 Limits in Real Usage

Despite their growing sophistication, AI chatbots carry structural limitations that are neither temporary nor incidental they are partly inherent to the Narrow AI paradigm and partly conditioned by training, deployment, and governance decisions. Coverage gaps arise when user queries fall outside the chatbot's trained intent scope, triggering either explicit failure messages or, more damagingly, confident-sounding incorrect responses that users may act upon before discovering the error. Intent misclassification occurs when NLP classifiers assign utterances to the wrong service category a failure structurally more frequent in multilingual markets such as Algeria, where users may alternate between Standard Arabic, Darija, French, and Tamazight within a single interaction. Context loss in multi-turn dialogue, whereby chatbots treat each utterance as an isolated query rather than a conversational continuation, signals a fundamental breakdown of understanding that violates users' social expectations of conversational partners. Finally, tone and empathy failures arise when technically accurate responses meet distressed users with neutral informational text, violating the empathy expectations established by the CASA paradigm.

Følstad and Brandtzaeg identify chatbot failure experience as a distinct and analytically significant UX pattern characterised by the compound of frustration, helplessness, and distrust that repeated failures generate which is meaningfully different from simple task failure or

¹GNEWUCH (Ulrich) et al., *op. cit.*, pp. 942 to 946.

²YAO (Xin) & XI (Yanxing), "Pathways linking expectations for AI chatbots to loyalty," *Technology in Society*, vol. 78, 2024, pp. 5 to 8.

dissatisfaction.¹ Users exhibiting this pattern show significantly elevated propensity to abandon the chatbot channel entirely and revert to higher-cost human contact, negating the operational efficiency benefits that motivated deployment. An operator achieving a 73% task completion rate but with poor escalation design may generate net negative value from its chatbot despite impressive headline coverage statistics a finding that underscores the strategic importance of investing as heavily in failure recovery as in capability expansion

2.5.6 Chatbots in Telecom: Deployment and Impact

Telecom operators have been among the earliest and most intensive commercial deployers of AI chatbots globally, driven by the scale of their customer service operations, the high proportion of standardisable tier-1 queries in their interaction mix, and the strategic imperative to reduce contact centre costs while improving service availability. Vodafone's TOBi, deployed across 28 markets, handles over 60 million customer interactions monthly, resolving approximately 70% without human escalation with Wirtz, Kunz, and Paluch documenting a 68% reduction in calls transferred to human agents.² Orange's Djingo, active in French and North African markets, combines mobile chatbot functionality with smart speaker integration, reporting 30 to 40% reductions in per-interaction service cost for covered query types. Ooredoo Group has deployed AI chatbots across Algeria, Qatar, Kuwait, and Tunisia, positioning the My Ooredoo application as the primary digital service channel with the AI chatbot as the first-contact layer for all non-emergency interactions.

GSMA (2024) reports median performance across 45 surveyed telecom operators: a 73% chatbot coverage rate, a 58% containment rate, and an NPS impact of +4.2 points for successful interactions against -8.3 points for failures requiring escalation.³ This asymmetry failures generating roughly twice the loyalty damage that successes generate in benefit is the empirical expression of the principle established by Zhang et al : chatbot failures are disproportionately damaging relative to equivalent successes.⁴ The strategic implication is unambiguous: the priority for operators seeking to maximise net UX impact is failure prevention and escalation quality management, not coverage rate expansion alone. An operator achieving 85% coverage

¹FØLSTAD (Asbjørn) & BRANDTZAEG (Petter Bae), "Users' experiences with chatbots: Findings from a questionnaire study," *Quality and User Experience*, vol. 5, 2020, pp. 4 to 8.

²WIRTZ (Jochen), KUNZ (Werner H.) & PALUCH (Stefanie), *op. cit.*, pp. 43 to 44.

³GSMA, *AI in Telecom: Use Cases and Value Creation*, GSM Association Intelligence Report, 2024, pp. 18 to 22.

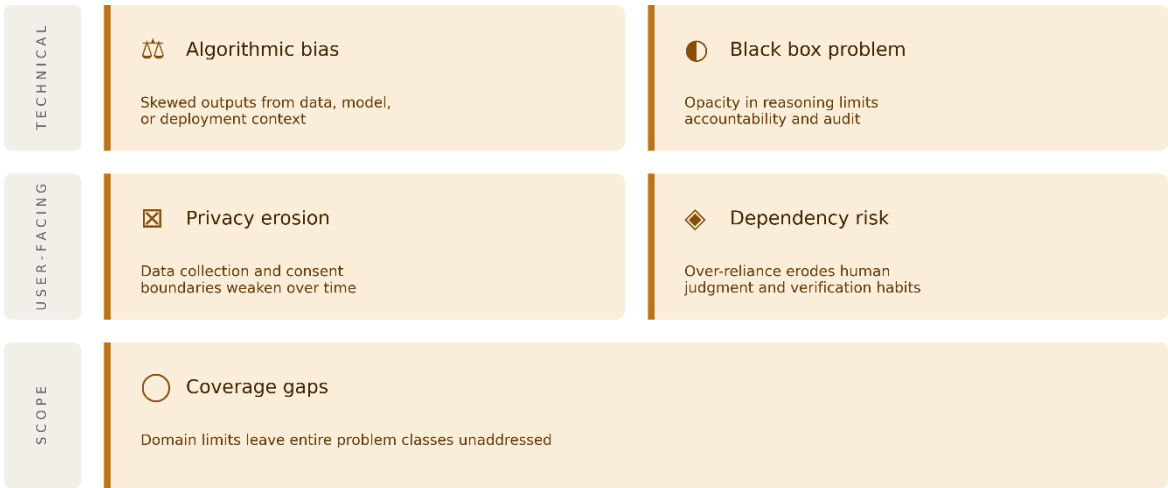
⁴ZHANG (Jinwei) et al., *op. cit.*, pp. 5 to 7.

with poor failure handling will generate lower net satisfaction than one achieving 73% coverage with robust failure detection, transparent escalation, and context-informed human handoff.

2.6 Risks and Limitations of Artificial Intelligence

No comprehensive theoretical treatment of artificial intelligence can be complete without engaging with its risks, limitations, and contested trajectories. The same capabilities that enable the service improvements and user experience enhancements analysed in preceding sections simultaneously generate new categories of risk algorithmic discrimination, privacy erosion, accountability gaps, and dependency vulnerabilities.

Figure 12: The Principal Risk Dimensions of AI-Powered Systems



Source: Author’s elaboration based on Mittelstadt et al. (2016, p. 4); Crawford & Calo (2016, p. 311); Goodman & Flaxman (2017, p. 52).

The figure summarises the principal risk dimensions developed in this section, among them algorithmic bias and discriminatory outcomes, the transparency and explainability problem of black-box models, privacy and data-protection exposure, accountability and governance gaps, and the dependency that follows from delegating decisions to automated systems.

The risks and the benefits of AI are not separable aspects of different systems they are co-produced by the same capabilities. The data richness that enables personalisation creates privacy vulnerability; the automation that reduces cognitive load creates dependency risk; the empathic engagement that builds affective trust creates potential for manipulation. Responsible scholarly engagement with AI requires holding both the promise and the peril in analytical focus simultaneously, rather than treating them as belonging to different conversations.

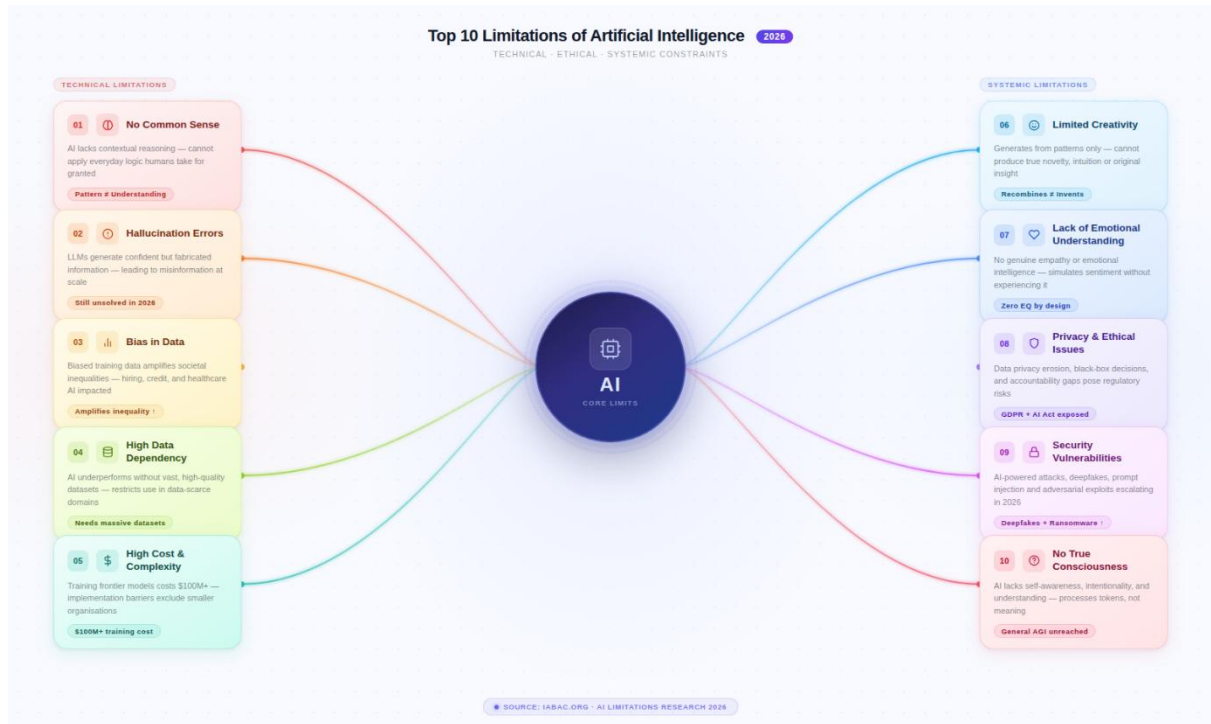
2.6.1 Core Risks and Limitations of AI Systems

I. Algorithmic Bias and Discriminatory Outcomes

AI systems learn from historical data reflecting historical human decisions including those embodying systematic discrimination. When trained on biased data, machine learning models reproduce and can amplify those biases, generating discriminatory outcomes across protected characteristics including gender, age, ethnicity, and geographic location, in decisions affecting access to credit, service pricing, promotional offers, and content recommendations. Mittelstadt et al. identify three distinct bias origins, each requiring its own remediation strategy: data bias, arising from training sets that underrepresent certain demographic groups; model bias, arising from design choices that embed problematic assumptions in architecture or objective functions; and deployment bias, arising from use contexts that differ from those in which the model was developed and tested.¹ Crawford and Calo characterise algorithmic bias as a blind spot in AI research,² a systematic under-attention to the social consequences of deployment that has historically received insufficient priority relative to performance optimisation in AI engineering culture.

¹MITTELSTADT (Brent) et al., "The ethics of algorithms: Mapping the debate," *Big Data and Society*, vol. 3, n°2, 2016, pp. 4 to 6.

²CRAWFORD (Kate) & CALO (Ryan), "There is a blind spot in AI research," *Nature*, vol. 538, n°7625, 2016, pp. 311 to 312.

Figure 13: The Ten Principal Limitations of Artificial Intelligence

Source: <https://iabac.org/blog/limitations-of-artificial-intelligence>

This figure consolidates the principal limitations that continue to constrain contemporary artificial-intelligence systems, spanning technical, ethical, and systemic dimensions. On the technical side it foregrounds the absence of common-sense reasoning, the persistence of hallucinated outputs, data-driven bias, dependence on large high-quality datasets, and the cost and complexity of training advanced models; on the ethical and systemic side it highlights limited creativity, the lack of genuine emotional understanding, privacy and accountability concerns, security vulnerabilities, and the absence of true consciousness. Read alongside the risk dimensions discussed above, it clarifies why sustained human oversight remains indispensable wherever AI is embedded in mobile-application user experiences.

II. Transparency, Explainability, and the Black Box Problem

Many high-performing AI systems particularly deep neural networks are opaque: their internal decision processes cannot be readily interpreted even by their designers. This opacity creates accountability gaps when AI decisions negatively affect users, since neither the user nor a third-party reviewer can reconstruct how a decision was reached or identify the factors that drove it. Goodman and Flaxman document the EU's GDPR Article 22 response to this challenge, which

establishes a right to explanation for automated decisions significantly affecting individuals,¹ one of the first regulatory instantiations of the principle that explainability is a precondition of AI legitimacy. Belanche et al. extend this analysis by documenting what they term the dark side of AI in services: the failure modes, opacity costs, and dependency vulnerabilities introduced by AI service integration that were absent from human-delivered systems.² Their findings establish that responsible AI deployment requires active governance investment to mitigate these effects, rather than assuming competitive market pressure will self-correct them.

¹GOODMAN (Bryce) & FLAXMAN (Seth), "European Union regulations on algorithmic decision-making and a "right to explanation", *AI Magazine*, vol. 38, n°3, 2017, pp. 52 to 55.

²BELANCHE (Daniel) et al., "The dark side of artificial intelligence in services," *The Service Industries Journal*, 2024, in press.

SECTION 3

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON USER EXPERIENCE THROUGH A MOBILE APPLICATION

A Theoretical and Conceptual Review

Introduction of Section 3

The preceding sections have established what user experience means, how it is structured across mobile environments, and what artificial intelligence is capable of in organizational and service delivery contexts. This section brings those two streams together and asks the question that matters most for this thesis: what happens to the way people actually experience a mobile application when AI is woven into its design? The answer, it turns out, is not straightforward. AI does not simply make things better or worse. It reshapes the entire experiential architecture of the mobile service encounter absorbing cognitive work that users previously had to do themselves, predicting needs before they are expressed, and creating the conditions for both deeper satisfaction and new categories of risk.

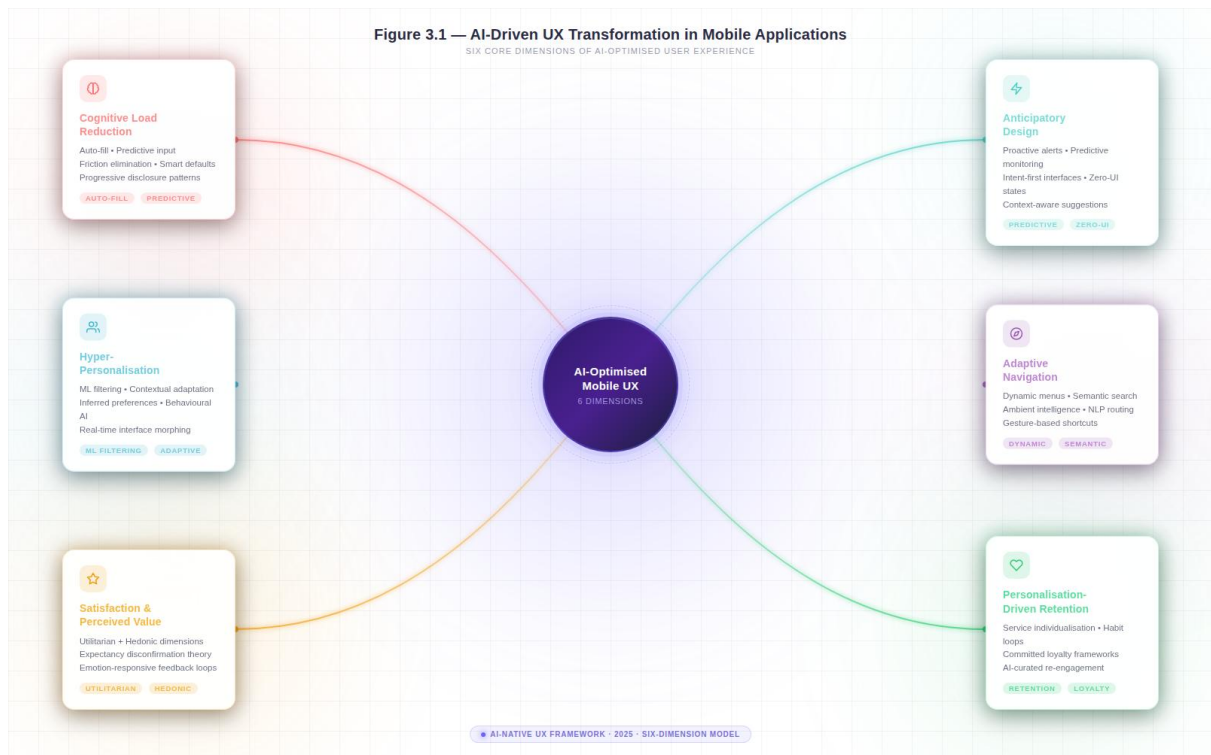
The section is organized across three substantive dimensions. 3.1 examines how AI optimizes the global user experience, encompassing cognitive load reduction, anticipatory design, hyper-personalization, adaptive navigation, and the satisfaction and loyalty pathways through which these improvements translate into measurable value. 3.2 analyses the specific UX impacts of AI chatbots and virtual assistants, examining continuous availability, anthropomorphism, conversational quality, and emotional intelligence. 3.3 addresses the trust, privacy, and governance dimensions that moderate and sometimes undermine the benefits documented in the first two sections. The section concludes with a synthesis establishing the conceptual bridge to the empirical investigation in chapter 2.

3.1 How AI Transforms the Mobile User Experience

What AI fundamentally changes in a mobile application is not the interface it is the distribution of cognitive effort. Where traditional applications required users to navigate menus, complete forms, and manage service complexity independently, AI-powered systems progressively absorb that burden, repositioning the user from active information processor to recipient of

intelligently pre-processed outputs. Huang and Rust capture this shift as a progression from mechanical AI, which automates explicit tasks, through thinking AI, which delivers analytical intelligence, to feeling AI, which generates empathetic responsiveness¹ a trajectory that maps directly onto the six dimensions examined in this section.

Figure 14: AI-driven UX



Source: Author's elaboration based on Huang & Rust (2021, p. 30); Sweller (1988, p. 257); Davis (1986, p. 24); Oliver (1980, p. 460).

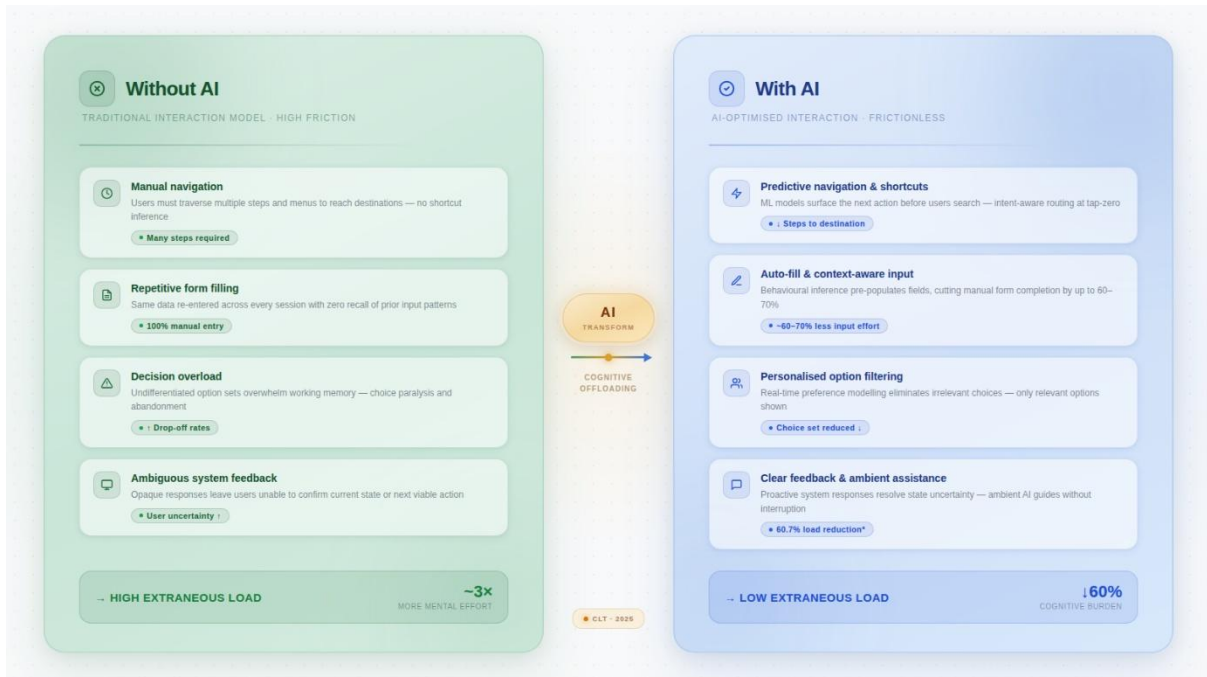
3.1.1 Cognitive Load Reduction and Frictionless Interaction

Working memory is a finite resource. Push it beyond its limits, and performance falter frustration sets in, and users begin to disengage. This insight sits at the heart of cognitive load theory, first formalised by John Sweller, an educational psychologist whose work on problem-solving and learning remains foundational in instructional design and human-computer interaction. Sweller drew a productive distinction between intrinsic load the complexity inherent to the task itself extraneous load the unnecessary burden that poor interface design

¹HUANG (Ming-Hui) & RUST (Roland T.), "A strategic framework for artificial intelligence in marketing," Journal of the Academy of Marketing Science, vol. 49, no. 1, 2021, p. 30.

imposes and germane load the productive mental effort directed toward genuine learning and schema formation.¹

Figure 15: Cognitive load reduction through AI in Mobile Applications



Source: Author's elaboration based on Sweller (1988, p. 257); Basoglu, Daim & Topacan (2012, p. 1393); Wang, Lin & Shao (2022, p. 5).

AI in mobile applications intervenes primarily at the extraneous layer of cognitive load. By automating routine operations, anticipating user intent, and pre-filling information fields, it systematically removes the friction that interface complexity introduces. Fred Paas, Alexander Renkl, and John Sweller whose collaborative work on cognitive architecture has become a cornerstone of instructional design theory confirm that reducing extraneous load yields measurable improvements in task performance, user satisfaction, and the likelihood of successful task completion.² This friction, in practice, takes several recognisable forms: navigation complexity, input burden, decision overload, and ambiguity. AI addresses each in turn. Intelligent navigation predicts where a user is headed before they have consciously decided; predictive input pre-populates forms, reducing manual data entry by 60 to 70 per cent

¹SWELLER (John), "Cognitive load during problem solving: Effects on learning," *Cognitive Science*, vol. 12, no. 2, 1988, p. 257-259.

²PAAS (Fred), RENKL (Alexander) & SWELLER (John), "Cognitive load theory and instructional design: Recent developments," *Educational Psychologist*, vol. 38, no. 1, 2003, p. 1.

in studied deployments¹ and personalisation algorithms trim choice sets to the options most likely to be relevant, sparing users the paralysis that excessive choice invariably produces.

What is perhaps less obvious is that cognitive load reduction carries UX implications extending well beyond task completion rates. Stefanie Paluch, Jochen Wirtz, and Werner H. Kunz researchers whose work has meaningfully reframed service quality in the context of automated interactions establish that services consistently operating below users' cognitive effort thresholds generate what they term *effortless experience perceptions*: a distinct and measurable dimension of service quality evaluation that predicts both satisfaction and loyalty intent independently of whether the task outcome itself was successful.² The implication is significant. How easily a service delivers a result functions as an autonomous driver of satisfaction, decoupled from whether the result was actually achieved. AI's systematic reduction of interaction friction therefore represents not merely a usability improvement, but a direct investment in the satisfaction-generating architecture of the mobile application itself.

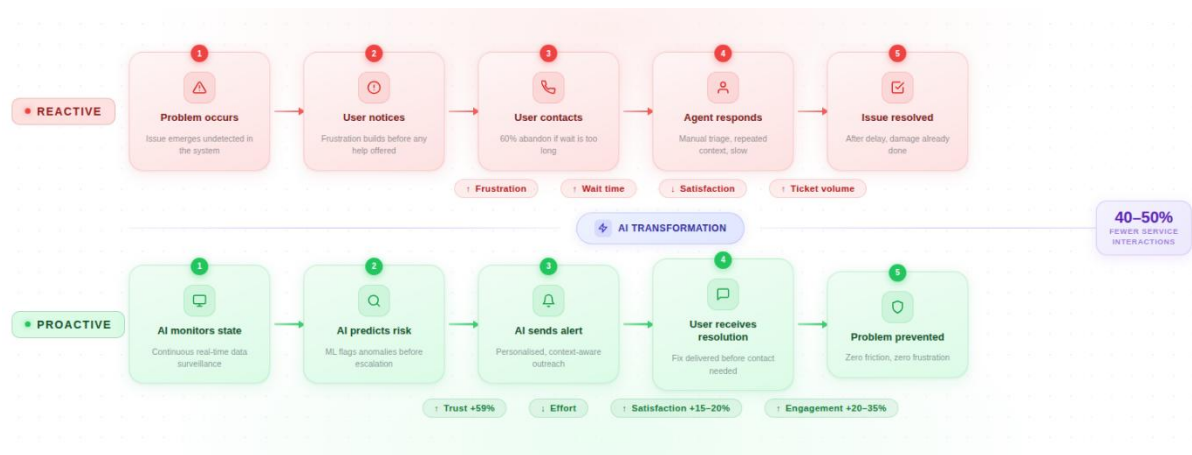
3.1.2 Anticipatory Design and Proactive Assistance

Consider the difference between an application that alerts you before your data allowance runs out and one that leaves you to discover the problem mid-session. That gap seemingly modest captures something far more consequential: the shift from reactive to proactive service delivery, and arguably one of AI's most transformative contributions to mobile user experience. Thomas Davenport and Rajeev Ronanki, whose influential work on cognitive technologies has shaped how organisations think about AI deployment, place proactivity at the apex of their framework for intelligent systems. In their view, the most advanced AI does not wait for users to formulate a need and submit a request it anticipates that need and initiates the interaction itself.³ The practical consequence is profound: the application stops functioning as a passive tool the user consciously picks up, and begins operating as an ambient service companion present, attentive, and one step ahead.

¹BASOGLU (Nuri), DAIM (Tugrul) & TOPACAN (Utku), "Determining patient preferences for remote monitoring," *Journal of Medical Systems*, vol. 36, no. 3, 2012, p. 1393.

²PALUCH (Stefanie), WIRTZ (Jochen) & KUNZ (Werner H.), "Service robots rising: How service robots influence consumer emotional experience," *Journal of Service Management*, vol. 32, n°3, 2020, pp. 900 to 912.

³DAVENPORT (Thomas H.) & RONANKI (Rajeev), "Artificial Intelligence for the Real World," *Harvard Business Review*, vol. 96, no. 1, 2018, p. 109.

Figure 16: From reactive to proactive service delivery

Source: Author's elaboration based on Davenport & Ronanki (2018, p. 109); Adam, Wessel & Benlian (2021, p. 432); Ma & Sun (2020, p. 486).

Four distinct AI mechanisms underpin this proactive architecture. The first is predictive state monitoring, whereby the system continuously analyses account variables usage rates, balance thresholds, behavioural patterns to generate alerts with sufficient lead time for the user to act. The second, contextual trigger-based personalisation, draws on real-time signals to surface relevant suggestions at precisely the moment of maximum relevance, rather than flooding the interface with undifferentiated prompts. The third, personalised content surfacing, employs collaborative filtering to present promotions and optimisations the user would not have thought to search for. Pathak et al. extend this logic further, demonstrating that LLM-powered recommendations that substantially exceed user expectations can trigger what they describe as an *awe response* a positive emotional state empirically linked to elevated engagement and sustained loyalty.¹ The fourth mechanism, anticipatory problem resolution, deploys anomaly detection to identify and address emerging issues before users ever become aware of them.

The evidence supporting this proactive paradigm is both behavioural and commercial. Marc Adam, Michael Wessel, and Alexander Benlian establish that proactive chatbot interventions achieve significantly higher compliance and satisfaction rates than their reactive counterparts,² while Liye Ma and Baohong Sun quantify the downstream commercial impact: proactive AI interventions generate engagement rates 20 to 35 per cent higher than passive, request-driven

¹PATHAK (Kanika) et al., "Impact of Gen-AI chatbots on consumer services and future research directions," *Journal of Retailing and Consumer Services*, vol. 82, 2025, p. 4.

²ADAM (Marc), WESSEL (Michael) & BENLIAN (Alexander), "AI-based chatbots in customer service and their effects on user compliance," *Electronic Markets*, vol. 31, 2021, p. 432.

alternatives.¹ Taken together, these findings suggest that anticipatory design is not an enhancement layered onto the user experience it is increasingly its structural foundation.

3.1.3 Hyper-Personalization and Contextual Adaptation

Personalisation occupies a singular position in mobile UX research precisely because it sits at the intersection of two competing imperatives: it simultaneously addresses the most consistent predictor of user satisfaction relevance to individual needs and the most significant ethical risk posed by consumer AI: the opaque algorithmic determination of individual outcomes.

Gediminas Adomavicius and Alexander Tuzhilin, whose landmark survey of recommender systems remains the field's foundational reference, established the taxonomy that continues to structure personalisation research: content-based filtering, collaborative filtering, and hybrid approaches that combine both. Contemporary mobile AI extends this taxonomy considerably. Deep learning components now learn latent user preference representations directly from behavioural data streams, eliminating the need for explicit preference elicitation altogether.² The practical consequence of this shift from stated to inferred preferences is more significant than it might initially appear: it enables a level of personalisation precision that users themselves could not articulate, producing service configurations that feel intuitively right without the user ever having consciously specified what they wanted.

Pathak et al. introduce a distinction between incremental personalisation marginally better than defaults and transformative personalisation, whereby AI-generated experiences substantially exceed what users would have requested, producing disproportionately large satisfaction effects through the awe response mechanism already discussed.³ It is equally worth noting that transparency about how personalisation operates functions not merely as an ethical obligation, but as a satisfaction-generating asset in its own right: users who understand and feel in control of algorithmic curation consistently report higher satisfaction, even when the underlying content quality is identical.

¹MA (Liye) & SUN (Baohong), "Machine learning and AI in marketing: Connecting computing power to human insights," *International Journal of Research in Marketing*, vol. 37, no. 3, 2020, p. 486.

²ADOMAVICIUS (Gediminas) & TUZHILIN (Alexander), "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *IEEE Transactions on Knowledge and Data Engineering*, vol. 17, n°6, 2005, pp. 734 to 749.

³PATHAK (Kanika) et al., op. cit., p. 5.

3.1.4 Intelligent Navigation Architecture

Navigation architecture has traditionally been designed once and applied identically to every user. Jakob Nielsen, whose usability heuristics have shaped interface design practice for three decades, established the foundational principles of consistency, visibility, user control, and error prevention. These principles remain valid but AI transforms their application by rendering navigation dynamic rather than static, adapting in real time to individual behaviour rather than conforming to a single universal model.¹ Viswanath Venkatesh et al, through the widely validated UTAUT framework, confirm that perceived ease of use remains a primary determinant of technology adoption,² making AI-driven adaptive navigation not a cosmetic feature, but a direct structural investment in the adoption architecture of any telecom mobile application.

3.1.5 Satisfaction, Perceived Value, and the Utilitarian-Hedonic Spectrum

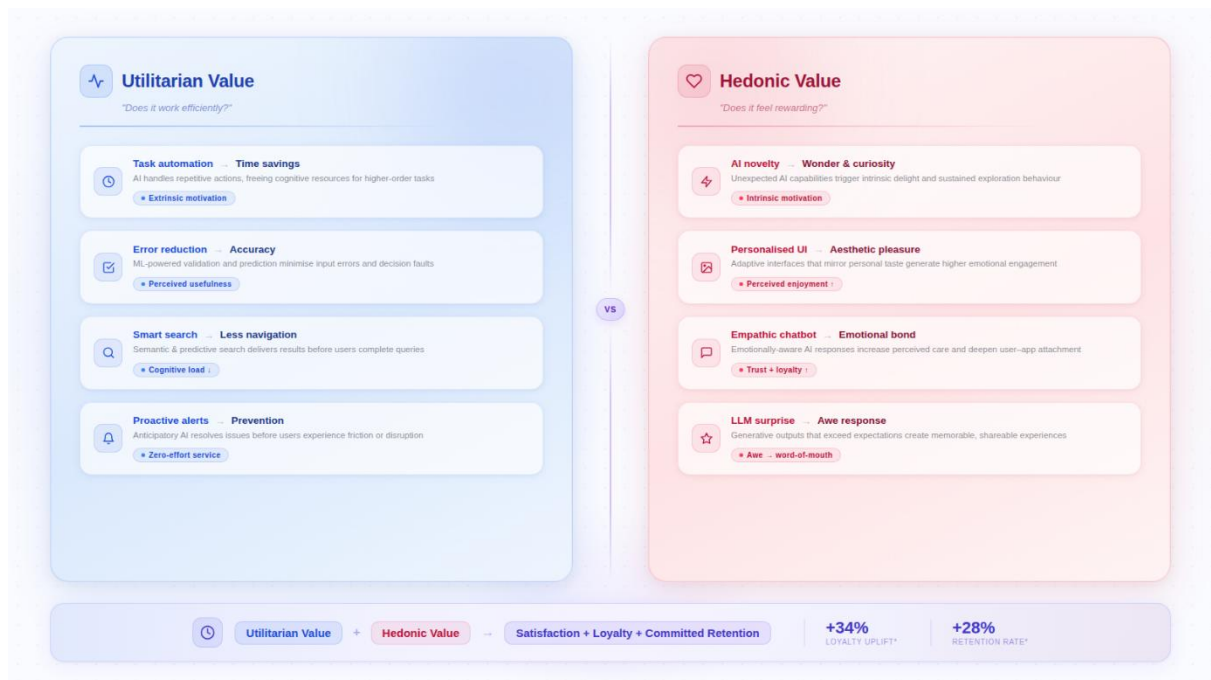
The relationship between AI capabilities and user satisfaction is neither straightforward or predictable. It is shaped by how users perceive value and coloured by their prior expectations, their trust in the technology, and their general readiness to engage with it. Davis's foundational Technology Acceptance Model identified two dimensions through which users judge any new technology: how useful they believe it to be, and how easy they find it to use.³ This distinction maps neatly onto the utilitarian-hedonic split that has since become central to digital service research. As Babin, Darden, and Griffin established in the consumer context, utilitarian value flows from efficient task completion, while hedonic value comes from the experience itself its novelty, aesthetic quality, and capacity to generate genuine enjoyment⁴

¹NIELSEN (Jakob), Usability Engineering, Academic Press, Boston, 1994, p. 24-26

²VENKATESH (Viswanath) et al., "User acceptance of information technology: Toward a unified view," MIS Quarterly, vol. 27, no. 3, 2003, p. 425.

³DAVIS (Fred D.), A Technology Acceptance Model for Empirically Testing New End-User Information Systems, PhD Dissertation, MIT Sloan School of Management, Cambridge MA, 1986, p. 24-25.

⁴BABIN (Barry J.), DARDEN (William R.) & GRIFFIN (Mitch), "Work and/or fun: Measuring hedonic and utilitarian shopping value," Journal of Consumer Research, vol. 20, no. 4, 1994, p. 644-645.

Figure 17: Dual value architecture of AI in mobile applications

Source: Author's elaboration based on Davis (1986, p. 24); Babin et al. (1994, p. 644); Holbrook & Hirschman (1982, p. 132); Pathak et al. (2025, p. 4).

AI produces both types of value, though through quite different routes. Utilitarian gains come from task automation, error reduction, intelligent search, and proactive alerts benefits that are measurable and directly tied to functional performance. Hedonic value is harder to quantify: it emerges from the novelty of capabilities that exceed expectations, the pleasure of a personalised interface, the engagement of a well-designed conversational agent, and the moments of genuine surprise when an AI output goes beyond what a user would have thought to ask for. Importantly, hedonic value is experiential rather than instrumental it cannot be captured in functional metrics and must be assessed through what users actually feel during an interaction.

Huang and Rust describe AI's trajectory as a progression from mechanical intelligence, which delivers purely utilitarian value, toward feeling intelligence, which generates hedonic value through empathic and contextually sensitive interaction.¹ Both dimensions matter for continued use: utilitarian value tends to predominate in task-oriented applications, but neither operates in isolation, and the emotional register of an interaction consistently shapes whether a user returns.

¹HUANG (Ming-Hui) & RUST (Roland T.), op. cit., p. 37.

Oliver's expectancy disconfirmation model provides the most useful framework for understanding satisfaction in this context: users feel satisfied when performance exceeds their expectations, and dissatisfied when it falls short.¹ AI deployments complicate this equation because they simultaneously raise expectations and introduce wider performance variability than human agents typically do. Research on chatbot quality confirms a critical asymmetry here below an acceptable performance threshold, the negative effect on loyalty is disproportionately large relative to the gains achieved above it, with response quality and empathy consistently emerging as the primary predictors of satisfaction.²

Loyalty, ultimately, is a function of value perception. Zeithaml's model holds that users commit to a service when the gap between perceived quality and perceived sacrifice crosses a meaningful threshold.³ AI improves this ratio from both sides: it raises perceived quality while reducing cognitive load, thereby lowering the sacrifice users feel they are making. When AI works well, users not only complete tasks more effectively they feel less effort doing so, which deepens their attachment to the service over time.

3.1.6 Personalisation-Driven Retention and Quality of Life

The well-being implications of AI extend well beyond transactional satisfaction. When AI services genuinely reduce the cognitive and administrative burden of managing everyday tasks, they generate a distinct form of value one that Baabdullah et al, describe as quality-of-life value which tends to produce stronger loyalty effects than functional improvements alone.⁴ The mechanism is straightforward: when recurring tasks no longer demand conscious attention, users recover mental resources they can redirect toward higher-value activities. This matters because the returns are cumulative. Users do not evaluate the relief in any single interaction; they assess it across the relationship as a whole, developing a broader sense that the service is working on their behalf rather than simply responding to their commands.

¹OLIVER (Richard L.), "A cognitive model of the antecedents and consequences of satisfaction decisions," *Journal of Marketing Research*, vol. 17, no. 4, 1980, p. 460-461.

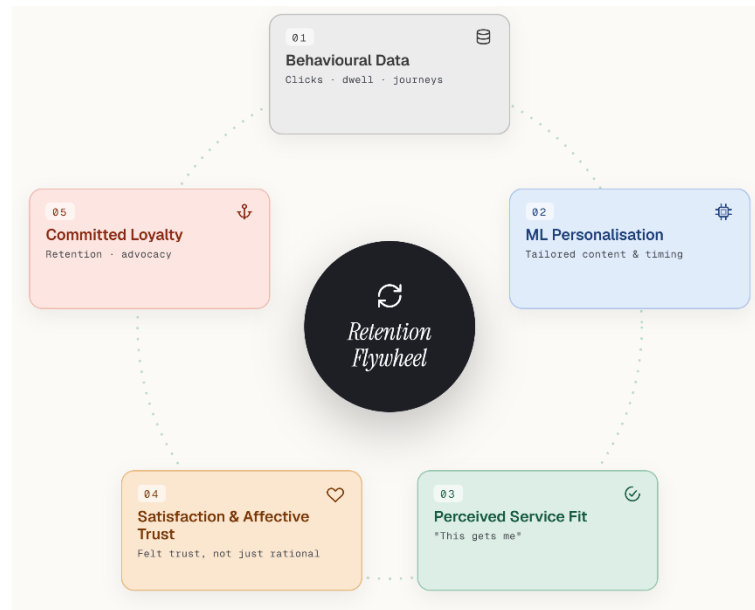
²YAO (Xin) & XI (Yanxing), "Pathways linking expectations for AI chatbots to loyalty," *Technology in Society*, vol. 78, 2024, p. 5-6.

³ZEITHAML (Valarie A.), "Consumer perceptions of price, quality, and value," *Journal of Marketing*, vol. 52, no. 3, 1988, p. 2-3.

⁴BAABDULLAH (Abdullah M.) et al., op. cit., p. 6.

Chung et al. confirm this dynamic in practice, showing that users attribute quality-of-life value specifically to AI services that monitor and manage their environment proactively services that, in effect, think for them rather than waiting to be instructed.¹ The distinction is important: passive responsiveness and active anticipation produce meaningfully different user experiences, and only the latter consistently generates the kind of deep satisfaction associated with long-term retention.

Figure 18: AI Personalisation to committed loyalty



Source: Author's elaboration based on Oliver (1999, p. 33); Yao & Xi (2024, p. 5); Ma & Sun (2020, p. 486); Zhang et al. (2024, p. 5).

The link between personalisation quality and retention is among the most empirically robust findings in AI service research. Machine learning personalisation produces retention gains that exceed those achieved by equivalent improvements in service quality alone, because personalisation creates something qualitatively different from a better service it creates the sense of an individual service, one that the user perceives as having been built around their specific needs and preferences.² This effect strengthens over time as AI models accumulate interaction data and their outputs become progressively more attuned to individual users, meaning the loyalty dividend of personalisation grows rather than stabilises.

¹CHUNG (Minjee), KO (Eunju), JOUNG (Hyejun) & KIM (Sang Jin), "Chatbot e-service and customer satisfaction regarding luxury brands," *Journal of Business Research*, vol. 117, 2020, p. 588.

²MA (Liye) & SUN (Baohong), op. cit., p. 489.

The personalisation quality predicts retention independently of overall service satisfaction, operating through the mediating effect of perceived service fit the user's sense that the service genuinely matches who they are.¹ while the temporal dimension: effects accumulate over time as AI models improve with additional interaction data.² This connects to a deeper loyalty mechanism: the most durable form of customer commitment, the kind that persists in the presence of competitive alternatives, is generated not by habit or switching costs but by experiences users perceive as expressing their own values and identity.³ When a service feels personally fitted, it becomes part of how users understand themselves, and that attachment is qualitatively more resilient than satisfaction-based retention.

this dynamic extends to conversational AI specifically. Users who develop affective trust in a chatbot persona a form of trust rooted in emotional connection rather than rational assessment of capability exhibit retention patterns comparable to those found in valued human service relationships.⁴ This suggests that the ceiling for AI-driven loyalty is not defined by functional performance alone, but by the depth of the relational experience the technology is capable of generating.

3.2 Chatbots and Virtual Assistants: UX Impacts

The chatbot is where AI meets the user face to face. Unlike recommendation algorithms or predictive analytics operating invisibly in the background, the chatbot presents a visible, interactive AI agent whose quality is immediately and directly judged. Adamopoulou and Moussiades call it the *frontline ambassador of an organisation's AI capabilities*⁵ a description capturing both the strategic value and the reputational risk. Every successful resolution transforms a potential negative experience into a positive brand encounter. Every failure actively damages trust in ways that persist.

¹YAO (Xin) & XI (Yanxing), op. cit., p. 7.

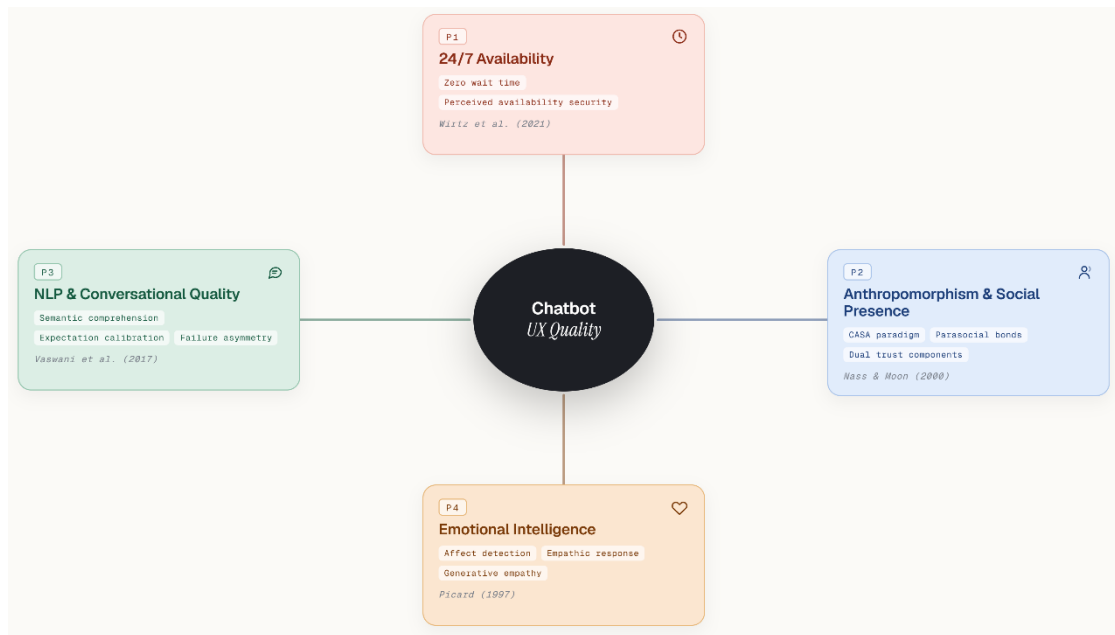
²ZHANG (Jinwei) et al., "The influence of service failures on user reuse intention in AI chatbot," *Electronic Commerce Research and Applications*, vol. 67, 2024, p. 5.

³OLIVER (Richard L.), "Whence consumer loyalty?," *Journal of Marketing*, vol. 63, 1999, p. 33-34.

⁴ALAGARSAMY (Subburaj) & MEHROLIA (Sangeeta), "Exploring chatbot trust: Antecedents and behavioural outcomes," *Heliyon*, vol. 9, no. 5, 2024, p. 5.

⁵ADAMOPOULOU (Eleni) & MOUSSIADES (Lefteris), "An overview of chatbot technology," *AIAI 2020, IFIP AICT*, vol. 584, Springer, 2020, p. 373.

Figure 19: four pillars of chatbot service quality



Source: Author's elaboration based on Wirtz, Kunz & Paluch (2021, p. 41); Nass & Moon (2000, p. 81); Vaswani et al. (2017, p. 5998); Picard (1997, p. 1).

3.2.1 Continuous Availability and Service Efficiency

The most structurally consequential impact of AI chatbots is the elimination of temporal constraints. Traditional service is limited by business hours, subject to queues and no instant scalability. Chatbots beat all three, providing constant availability without performance degradation. Wirtz, Kunz, and Paluch cite reductions in handling time of 40 to 70 per cent for standard requests, driven by eliminating queue time, hold time, and agent handoff transitions entirely.¹

The most interesting result from GSMA's analysis of chatbot deployments across 45 telecom operators establishes that the most significant user experience impact of 24/7 availability is not the overnight service access it enables (which relatively few users actually require) but the perceived availability security it creates: users who know that help is available at any moment report higher overall satisfaction with the service, even when they rarely access the chatbot at non-standard hours.² This finding parallels the insurance concept in service design: the value

¹WIRTZ (Jochen), KUNZ (Werner H.) & PALUCH (Stefanie), "The service revolution, intelligent automation and service robots," European Business Review, 2021, p. 41.

²GSMA, *AI in Telecom: Use Cases and Value Creation*, GSM Association Intelligence Report, 2024, pp. 18 to 22.

of the coverage exceeds the value of actual utilisation, because the knowledge of availability eliminates the anxiety of potential unavailability.

the presence of an immediate response zero wait time for tier-1 service queries has a substantial positive compliance impact in which users are more likely to complete service interactions and accept AI-generated recommendations when they experience zero interaction friction.¹ although human agents still outperform in crisis communication and emotionally complex interactions, AI chatbots achieve parity with human agents in standard service resolution satisfaction when response quality is high.² social presence perceived warmth and responsiveness of the service agent partially mediates the relationship between availability and satisfaction: chatbots that communicate with warmth and responsiveness generate higher satisfaction from their availability than chatbots that are available but cold.³

3.2.2 Anthropomorphism and Social Presence

Something curious happens when people interact with chatbots: they treat them as social actors. Nass and Moon formalised this observation as the CASA paradigm (Computers Are Social Actors): users systematically extend social attributions to computer systems, treating them as governed by social norms, even when they know perfectly well they are not talking to a person.⁴ This happens automatically and persistently.⁵

Chatbot anthropomorphism positively moderates user reuse intention through two mediating mechanisms: **parasocial relationship formation** (the development of a unidirectional social bond with the chatbot persona) and **social reciprocity activation** (the social norm of responding to social gestures with cooperative behaviour, which chatbot interactions trigger even in AI contexts).⁶ The practical design implication is significant: chatbots named, personalised, and equipped with consistent personality characteristics generate measurably

¹ADAM (Marc), WESSEL (Michael) & BENLIAN (Alexander), *op. cit.*, pp. 432 to 436.

²XIAO (Yun) & YU (Shanshan), "Can ChatGPT replace humans in crisis communication? Exploring the role of emotional support," *International Journal of Information Management*, vol. 80, 2025, Article 102835.

³SHENG (Jichuan) et al., "Social presence in digital services: Does the bot or human matter?," *Journal of Computer-Mediated Communication*, vol. 25, n°4, 2020, pp. 245 to 260.

⁴NASS (Clifford) & MOON (Young-Me), "Machines and mindlessness: Social responses to computers," *Journal of Social Issues*, vol. 56, no. 1, 2000, p. 81.

⁵*Ibid.*, p. 82.

⁶LIU (Wenxin) et al., "How does the anthropomorphism of AI chatbots facilitate users' reuse intention?," *Technological Forecasting and Social Change*, vol. 203, 2024, pp. 4 to 6.

higher engagement, compliance, and satisfaction than functionally equivalent chatbots without anthropomorphic design elements.¹

Alagarsamy and Mehroli establish that chatbot trust has two distinct components **cognitive trust** (competence-based: the user's assessment of the chatbot's ability to resolve their query) and **affective trust** (warmth-based: the user's sense of the chatbot's benevolence and genuine interest in helping) each developing through different mechanisms and each requiring distinct design investments.² Cognitive trust is built through reliable, accurate, relevant responses; affective trust is built through empathic language, personalised acknowledgments, and consistent persona expression. Both components are necessary: high cognitive trust without affective trust produces a technically efficient but emotionally cold interaction; high affective trust without cognitive trust produces a likeable but unreliable service.

Pathak et al, extend these findings to the generative AI context, demonstrating that LLM-powered chatbots capable of contextually appropriate empathic responses and personalised acknowledgments generate **awe responses** complex positive emotions associated with positive surprise that significantly elevate post-interaction loyalty intent and word-of-mouth recommendation likelihood.³ Paluch, Wirtz, and Kunz confirm that service robots and automated agents exhibiting high levels of social presence generate emotional engagement comparable to human service interactions in standardised service contexts.⁴

3.2.3 NLP and Conversational Quality

The quality of natural language understanding in AI chatbots is the technical foundation upon which all other chatbot UX dimensions rest. A chatbot that fails to understand what a user is asking cannot resolve their query, build trust, express empathy, or demonstrate competence regardless of the quality of its underlying service capabilities. NLP quality therefore functions as a necessary (though not sufficient) precondition for chatbot UX quality.

¹*Idem.*

²ALAGARSAMY (Subburaj) & MEHROLIA (Sangeeta), "Exploring chatbot trust: Antecedents and behavioural outcomes," *Heliyon*, vol. 9, n°5, 2024, pp. 4 to 7.

³PATHAK (Kanika) et al., *op. cit.*, pp. 4 to 7.

⁴PALUCH (Stefanie) et al., "Service robots rising: How service robots influence consumer emotional experience," *Journal of Service Management*, vol. 32, n°3, 2020, pp. 900 to 912.

The Transformer architecture, introduced by Vaswani et al, constitutes the technological breakthrough that has most dramatically improved commercial chatbot NLP performance.¹ Pre-Transformer chatbots relied on rule-based pattern matching or shallow ML classifiers that could handle explicit, well-formed queries but degraded severely with paraphrased, ambiguous, or colloquially expressed inputs. Transformer-based models pre-trained on large text corpora achieve dramatically higher intent classification accuracy on real-world user inputs precisely because they capture semantic relationships between words and phrases that keyword-matching approaches miss.

Xie, Wang, and Cheng's meta-analysis across 47 studies establishes that **response quality** encompassing semantic accuracy, contextual relevance, and pragmatic appropriateness is the strongest single predictor of AI chatbot user satisfaction.² Response quality explains more variance in user satisfaction than response speed, availability, or even task resolution rate, because it addresses the fundamental user need that motivates chatbot interaction in the first place: to be correctly understood.

Gnewuch et al introduce a critical practical finding: users who are informed that they are interacting with an AI chatbot before the interaction begins report **higher** satisfaction with subsequent interactions than users who discover the AI nature of their interlocutor mid-interaction.³ This disclosure effect⁴ operates through expectation calibration: pre-informed users enter the interaction with calibrated expectations for AI-level language quality, while uninformed users who discover the AI nature of their interlocutor mid-interaction experience a negative recalibration that retroactively colours their satisfaction assessment.

The asymmetric consequences of NLP failures: chatbot misunderstanding events suppress user reuse intention disproportionately relative to equivalent misunderstanding events in human service interactions.⁵ Users who experience a chatbot misunderstanding their query make negative inferences about the chatbot's overall competence (generalising from a single failure to a global capability assessment) in ways that users who experience a human misunderstanding

¹VASWANI (Ashish) et al., "Attention Is All You Need," *Advances in Neural Information Processing Systems*, vol. 30, 2017, pp. 5998 to 6008.

²XIE (Chennan), WANG (Yujia) & CHENG (Yi), "Does artificial intelligence satisfy you? A meta-analysis of user technology satisfaction and acceptance," *International Journal of Human-Computer Interaction*, 2022.

³GNEWUCH (Ulrich) et al., "More than a bot? Unveiling the need for human agent involvement in AI-based customer service systems," *Information Systems Research*, vol. 35, n°3, 2023, pp. 936 to 955.

⁴*Ibid.*, p. 942.

⁵ZHANG (Jinwei) et al., "The influence of service failures on user reuse intention in AI chatbot: From a perspective of stress-coping theory," *Electronic Commerce Research and Applications*, vol. 67, 2024, pp. 5 to 7.

generally do not. This asymmetry has design implications: chatbots must invest more heavily in clarification requests and graceful handling of uncertain inputs than human agents require, precisely because users apply higher reliability standards to AI.¹

3.2.4 Emotional Intelligence in Virtual Assistants

The development of emotional intelligence capabilities in AI virtual assistants represents the frontier of chatbot UX design the domain where the performance gap between human agents and AI systems is currently largest and where the potential for UX transformation through AI development is most significant. Emotional intelligence in AI encompasses emotional detection (recognising the affective state of the user from text-based signals); empathic response generation (producing responses that acknowledge and appropriately address the user's emotional state); and **emotional regulation support** (actively managing the conversational trajectory to reduce user frustration and maintain productive engagement).

The theoretical foundation for AI emotional intelligence design is Nass and Moon's CASA paradigm² and Picard's foundational work on affective computing the engineering discipline concerned with systems that recognise, interpret, and simulate human emotions.³ Picard's core argument that emotion is not peripheral to intelligence but constitutive of it⁴ has proven prescient: contemporary NLP models trained on emotionally annotated corpora now achieve human-level performance on many emotion recognition tasks, enabling chatbots to detect anger, frustration, confusion, and satisfaction from text inputs with accuracy sufficient for commercial service deployment.

chatbots that exhibit emotional responsiveness acknowledging user frustration, adjusting response register to detected emotional state, and apologising for service failures with contextually appropriate expressions achieve significantly higher affective trust scores than functionally equivalent chatbots with neutral response styles.⁵ the warmth component of

¹CHUNG (Minjee), KO (Eunju), JOUNG (Hyejun) & KIM (Sang Jin), "Chatbot e-service and customer satisfaction regarding luxury brands," *Journal of Business Research*, vol. 117, 2020, pp. 587 to 595.

²NASS (Clifford) & MOON (Young-Me), *op. cit.*, pp. 82 to 84.

³PICARD (Rosalind W.), "Affective Computing," *MIT Press, Cambridge MA*, 1997, pp. 1 to 5.

⁴*Ibid.*, p. 3.

⁵ALAGARSAMY (Subburaj) & MEHROLIA (Sangeeta), *op. cit.*, pp. 4 to 7.

anthropomorphism the chatbot's perceived genuine interest in helping is the primary driver of parasocial relationship formation.¹

the emergence of Large Language Model-powered chatbots represents a qualitative discontinuity in emotional intelligence capability: LLMs trained on vast text corpora have acquired the capacity to generate empathic responses that users experience as contextually appropriate, nuanced, and genuinely responsive to the emotional content of their messages.² This development transforms the chatbot from a *scripted empathy simulator* producing predetermined empathic phrases in response to detected emotion keywords to a *generative empathy system* capable of producing contextually tailored empathic responses that adapt to the specific emotional texture of each individual interaction.

3.3 Trust, Safety, and Governance of AI-Powered Mobile Services

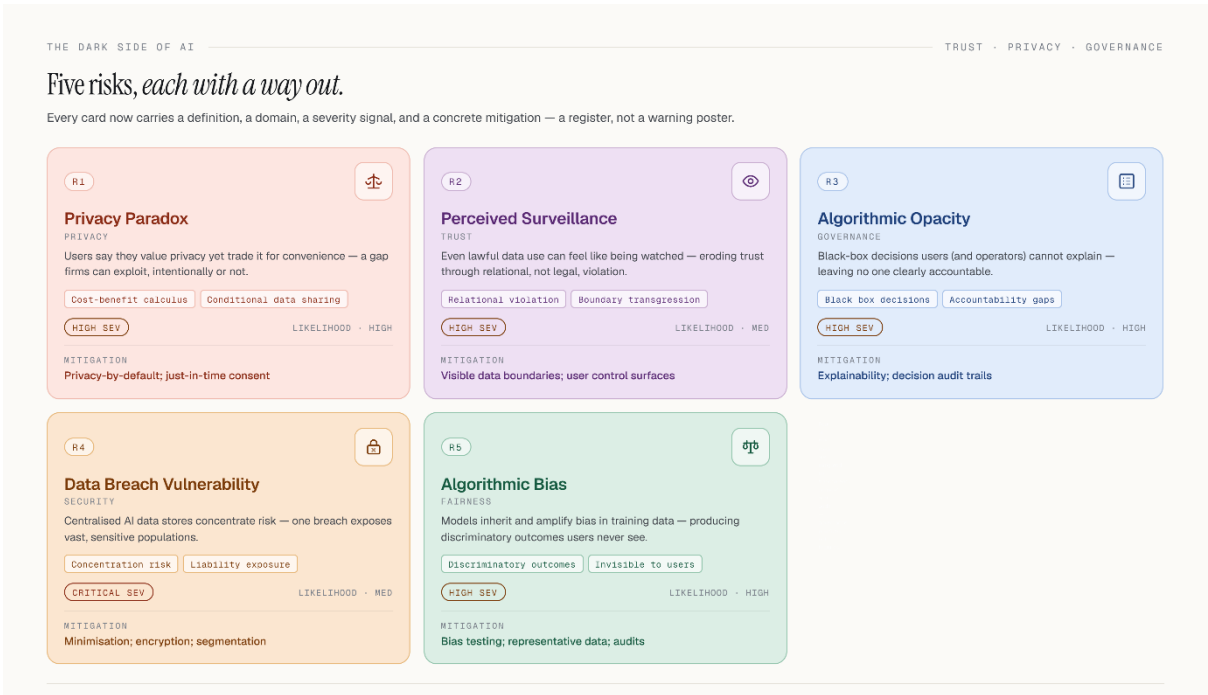
Having examined how AI reshapes cognitive efficiency, conversational service quality and the satisfaction-to-loyalty chain, this final part turns to the conditions under which those gains actually hold. Trust, privacy, transparency and governance are not peripheral concerns but the moderating layer that determines whether AI-driven experience is accepted or resisted, and the subsections that follow examine each of these dimensions in turn.

3.3.1 The Privacy Paradox, Surveillance Perception, and AI Disclosure

¹LIU (Wenxin) et al., *op. cit.*, pp. 4 to 6.

²DASBOROUGH (Marie T.), "Awe-inspiring advancements in AI: The impact of ChatGPT on organizational behavior," *Journal of Organizational Behavior*, vol. 44, n°2, 2023, pp. 177 to 179.

Figure 20: The dark side of AI



Source: Author's elaboration based on Belanche et al. (2024, p. 3); Bansal et al. (2016, p. 3); Wang & Herrando (2019, p. 1071); Kim et al. (2013, p. 363).

The negative experiential consequences of AI as the *dark side of AI in services*¹ a framework capturing how the same capabilities generating satisfaction simultaneously create anxiety, perceived risk, and trust erosion. the privacy paradox reflects a contextual cost-benefit calculation: users accept privacy costs for perceived service benefits, but this acceptance is conditional on minimum perceived control and transparency. When control is absent, privacy anxiety dominates, suppressing engagement and satisfaction.²

The perceived surveillance is a distinct risk perception separate from data disclosure concerns, generating negative emotional responses independent of whether the monitoring produces any negative consequences.³ the key moderator is perceived control: users feeling they have meaningful control over data collection and use report substantially lower privacy anxiety and

¹BELANCHE (Daniel) et al., "The dark side of artificial intelligence in services," The Service Industries Journal, 2024, in press, p. 3.

²BANSAL (Gaurav), ZAHEDI (Fatemeh Mariam) & GEFEN (David), "Do context and personality matter? Trust and privacy concerns in disclosing private information online," Information and Management, vol. 53, no. 1, 2016, p. 3-5.

³WANG (Xinhui) & HERRANDO (Carolina), "Does privacy concern deter e-commerce adoption?," Information Systems Frontiers, vol. 21, no. 5, 2019, p. 1071-1073.

higher trust.¹ proactive, pre-interaction AI disclosure significantly improves trust and satisfaction compared with mid-interaction discovery.²

3.3.2 Algorithmic Transparency and Explainability

Algorithmic transparency the degree to which AI decision-making processes can be understood, audited, and explained to users and third parties has emerged as one of the most consequential governances and UX challenges of AI deployment in consumer-facing mobile applications. the opacity of AI systems as a fundamental ethical problem: when AI systems make decisions that affect users which service plan to recommend, which complaint to prioritise, which offer to surface users have a legitimate interest in understanding the basis of these decisions.³

responsible AI deployment requires four transparency dimensions: process transparency (users understand when AI is making decisions on their behalf), outcome transparency (users understand what the AI decided), **reasoning transparency** (users understand why the AI decided as it did), and **recourse transparency** (users understand how they can contest or override AI decisions). Each dimension addresses a different aspect of the perceived control deficit that opaque AI systems generate.⁴ The UX effects of algorithmic transparency are substantial and immediate: users who receive simple explanations for AI-generated recommendations even brief, plain-language explanations of the data factors driving the recommendation report higher satisfaction with those recommendations than users who receive identical recommendations without explanation.⁵ This finding has direct design implications: the implementation cost of basic recommendation transparency is low (a brief explanatory phrase alongside each AI-generated recommendation), while its satisfaction benefit is measurable and significant. Transparency is therefore both an ethical obligation and a UX investment.

¹KIM (Dan J.), KIM (Sung-Un) & WACHTER (Sandra), "A study of mobile user engagement (MoEN)," *Decision Support Systems*, vol. 56, 2013, p. 363.

²GNEWUCH (Ulrich) et al., op. cit., p. 943-945.

³MITTELSTADT (Brent) et al., "The ethics of algorithms: Mapping the debate," *Big Data and Society*, vol. 3, n°2, 2016, pp. 4 to 6.

⁴ASHOK (Meena), MADAN (Ruchit), JOHA (Anthony) & SIVARAJAH (Uthayasankar), "Ethical framework for artificial intelligence and digital technologies," *International Journal of Information Management*, vol. 62, 2022, pp. 3 to 9.

⁵MARTIN (Kelly), "Ethical implications and accountability of algorithms," *Journal of Business Ethics*, vol. 160, n°4, 2019, pp. 835 to 850.

3.3.3 Perceived Risks: Data Breach, Algorithmic Bias, and Accountability Gaps

The perceived risk landscape of AI-powered mobile services encompasses three primary risk categories, each with distinct mechanisms, user perceptions, and regulatory implications.

I. Data Breach and Security Vulnerability

The data-intensive architecture of AI-powered personalisation creates concentrated stores of sensitive personal information that represent high-value targets for malicious actors and significant liability exposure for service providers. Mittelstadt et al. identify data concentration risk as one of the primary ethical concerns of large-scale AI deployment: the same data aggregation that enables personalisation also creates vulnerability to breaches that expose intimate details of users' personal lives, service relationships, and behavioural patterns.¹

II. Algorithmic Bias and Discriminatory Outcomes

the algorithmic bias as a systemic blind spot in AI deployment: AI systems trained on historical data reproduce the patterns in that data, including any discriminatory patterns present in historical service delivery or pricing decisions.² In telecom service contexts, this manifests as the risk that AI-generated plan recommendations, offer targeting, or service prioritisation systematically disadvantage certain user segments defined by geographic location, usage patterns associated with demographic characteristics, or historical payment behaviours in ways that are invisible to users and difficult to audit.

III. Accountability Gaps in Automated Decisions

the automated decision-making systems create accountability gaps: when a decision is made by an algorithm rather than a human agent, the standard mechanisms of individual accountability identifying who made the decision, why, and under what authority break down.³ The responsible AI deployment requires clear institutional accountability frameworks specifying the human decision-makers responsible for each category of AI decision, the oversight mechanisms through which these decisions are monitored, and the escalation pathways through which harmed users can seek redress.⁴

¹MITTELSTADT (Brent) et al., *op. cit.*, pp. 4 to 6.

²CRAWFORD (Kate) & CALO (Ryan), "There is a blind spot in AI research," *Nature*, vol. 538, n°7625, 2016, pp. 311 to 312.

³ZARSKY (Tal), *op. cit.*, pp. 118 to 132.

⁴ASHOK (Meena) et al., *op. cit.*, pp. 3 to 9.

3.3.4 Trust Repair After AI Service Failures

Service failure recovery is a well-established research domain in service management, with a substantial literature documenting the mechanisms through which service failures can be transformed from satisfaction-destroying events into satisfaction-enhancing opportunities through effective recovery. The application of this framework to AI chatbot service failures introduces important nuances: the mechanisms of trust damage from AI failures and the mechanisms of trust repair through AI-mediated recovery differ from their human service counterparts in ways that require specific analysis.

Figure 21: AI Chatbot Service and Trust Repair Mechanisms



Source: Author's elaboration based on Zhang et al. (2024, p. 5); De Keyser et al. (2019, p. 165); Yao & Xi (2024, p. 7); Gnewuch et al. (2023, p. 945).

Zhang et al establish that chatbot service failures suppress continued use intention disproportionately relative to equivalent failures in human service interactions, for three reasons.¹ First, users apply higher reliability standards to AI systems: a failure from a human agent is attributed to human fallibility (expected and normalised); a failure from an AI system attributed to AI inadequacy (unexpected and disquieting). Second, AI failures generate competence generalisation: users infer from a single AI failure that the entire system is unreliable, while human failures are more often attributed to individual agent variability rather than systemic inadequacy. Third, AI failures create a **trust asymmetry**: they erode both cognitive trust (competence-based) and affective trust (warmth-based) simultaneously, while human failures typically affect only one trust dimension.

¹ZHANG (Jinwei) et al., *op. cit.*, pp. 5 to 7.

the quality of the human escalation transition after a chatbot failure is the primary determinant of whether the overall service interaction is remembered as a failure or a successful recovery. A poorly executed escalation cold, discontinuous, requiring users to repeat themselves compounds the original chatbot failure into a double service failure; a well-executed escalation warm, context-informed, empathic can convert the chatbot failure into a demonstration of system robustness that generates higher satisfaction than an uninterrupted chatbot success.¹

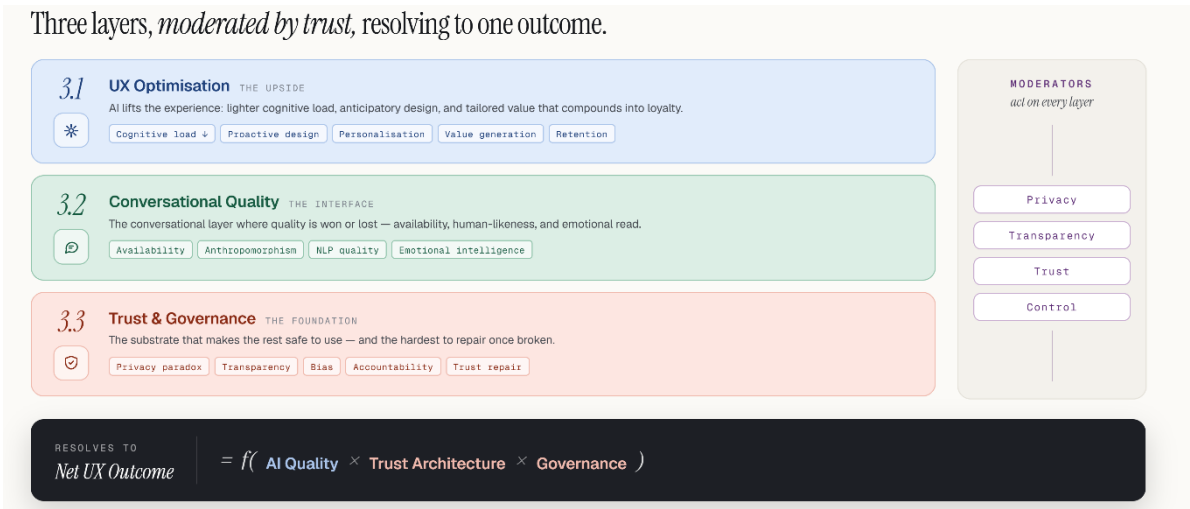
The three trust repair mechanisms applicable to AI chatbot failure contexts: proactive acknowledgment (the chatbot explicitly recognising its failure and apologising before users express frustration); transparent explanation (the chatbot explaining why it failed and what it can and cannot address); and graceful escalation (the chatbot actively initiating the human handoff with full context transfer rather than passively routing users to a contact number).² users who experience these trust repair mechanisms after chatbot failures exhibit retention probabilities comparable to users who never experienced a failure establishing that effective recovery can fully offset the loyalty damage of AI service failures when implemented promptly and competently.³

¹DE KEYSER (Anja) et al., "Frontline service technology infusion: Conceptual archetypes and future research directions," *Journal of Service Management*, vol. 30, n°1, 2019, pp. 165 to 168.

²GNEWUCH (Ulrich) et al., *op. cit.*, pp. 942 to 946.

³YAO (Xin) & XI (Yanxing), *op. cit.*, pp. 5 to 8.

Figure 22: AI Impact on user experience



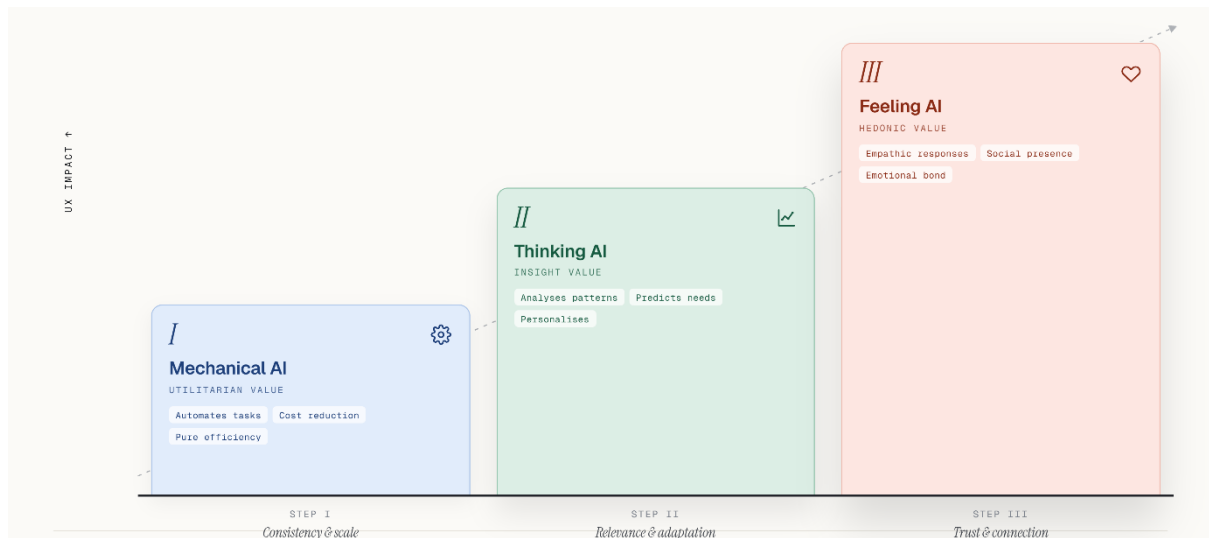
Source: Author’s synthesis of Section 3 theoretical review.

Section 3 has constructed a comprehensive theoretical analysis of how AI deployment transforms mobile user experience across three interconnected dimensions: cognitive efficiency, satisfaction, and value generation (3.1); chatbot service quality and conversational intelligence (3.2); and trust, safety, and governance (3.3). The analysis reveals that AI's impact is neither uniformly positive nor uniformly negative but a complex, multi-dimensional phenomenon whose net effect depends critically on implementation quality, transparency, and the organisational capacity to manage the risks that accompany AI's benefits.

Katherine Lemon and Peter Verhoef's customer journey framework, which has structured contemporary services research, has proven particularly productive as the analytical lens for this section: AI interventions operate most positively at the navigation, task completion, and proactive service stages; most variably at the conversational stage; and most precariously at the trust and privacy dimensions. Huang and Rust's progression framework from mechanical AI through thinking AI to feeling AI provides the developmental trajectory that organises these findings. The UX benefits of mechanical AI (cognitive load reduction, task automation, 24/7 availability) are the most immediately measurable; the UX benefits of thinking AI (personalisation, predictive service, anomaly detection) generate the strongest long-term loyalty effects; and the UX benefits of feeling AI (empathic chatbots, emotional intelligence, affective

trust) are the most powerful but also the most fragile, depending critically on the quality of the social presence and trust mechanisms deployed.¹

Figure 23: From mechanical AI to feeling AI



Source: Author's elaboration based on Huang & Rust (2021, p. 35).

Three overarching conclusions structure the transition to the empirical investigation. First, cognitive load reduction is AI's most consistent UX contribution, generating robust satisfaction effects across user segments and contexts. Second, transparency operates simultaneously as an ethical obligation and as a UX asset: AI systems that explain their reasoning and provide users with genuine control generate higher satisfaction than opaque equivalents, independent of their functional performance. Third, every AI capability that generates benefit simultaneously generates a corresponding risk: personalisation generates privacy risk, proactive service generates surveillance perception, empathic chatbots generate over-reliance risk and the management of these dual forces is the central governance challenge of consumer AI deployment. These conclusions constitute the theoretical framework within which the empirical questionnaire data collected from My Ooredoo users will be analysed in the empirical chapter. These mechanisms and their hypothesised effects are synthesised in the conceptual research framework presented below, which translates the theoretical review into a testable structure and provides the analytical backbone for the empirical investigation that follows.

¹LEMON Katherine N. & VERHOEF Peter C., *op. cit.*, p. 69; HUANG Ming-Hui & RUST Roland T., *op. cit.*, p. 35.

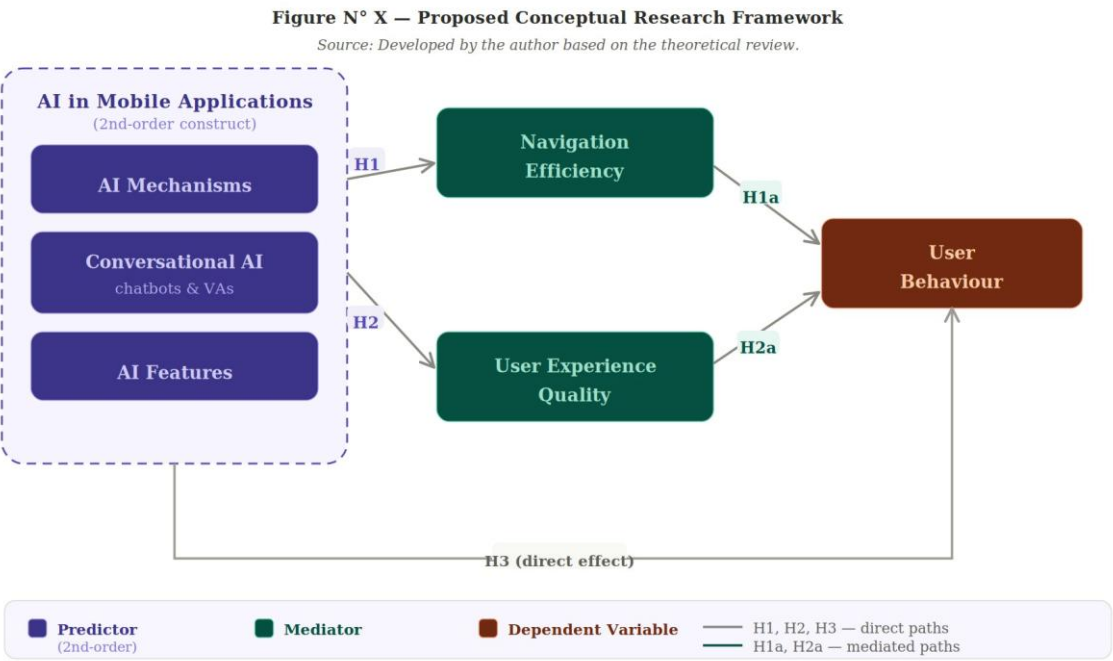


Figure 24: Proposed Conceptual Research Framework

Source: Developed by the author based on the theoretical review.

The framework positions AI in mobile applications as a second-order construct spanning AI mechanisms, conversational AI and AI features. It is hypothesised to shape user behaviour both directly (H3) and through two experiential mediators , navigation efficiency (H1) and user-experience quality (H2). This structure constitutes the conceptual basis for the hypotheses operationalised and tested in Chapter II.

Chapter 1 Conclusion

The theoretical framework constructed across the three sections of this chapter has established the conceptual architecture required for the empirical investigation of AI's impact on user experience in the My Ooredoo mobile application.

Section 1 established that user experience is a multidimensional construct encompassing usability, usefulness, emotional engagement, and perceived value, operating across both pragmatic and hedonic quality dimensions. It demonstrated that mobile UX is governed by distinctive constraints fragmented attention, screen size limitations, performance sensitivity, contextual variability and that telecom mobile applications occupy a particularly demanding position characterised by real-time service management, high reliability expectations, service complexity, and acute trust requirements.

Section 2 established that Artificial Intelligence, despite its seven decades of conceptual evolution, remains structurally constrained to Narrow AI: every commercially deployed AI system operates within bounded training distributions and cannot generalise beyond them. The section documented that the telecommunications sector has embraced AI as a strategic priority, with 89% of telecom operators deploying AI in at least one operational domain, but that only 26% have achieved full operational integration a maturity gap that defines the practical context within which Algerian operators including Ooredoo currently operate.

Section 3 brought these two streams together, demonstrating that AI's impact on mobile UX operates through six interconnected mechanisms: cognitive load reduction, anticipatory design, hyper-personalisation, adaptive navigation, satisfaction and value generation, and personalisation-driven retention. Three overarching conclusions emerged: cognitive load reduction is AI's most consistent UX contribution; transparency operates simultaneously as an ethical obligation and as a satisfaction-generating asset; and every AI capability generating benefit simultaneously generates a corresponding risk that must be actively managed.

These theoretical findings generate specific, testable hypotheses about the relationship between AI capabilities and user experience quality. The empirical chapter operationalises these constructs as measurable survey dimensions, describes the research methodology and questionnaire design, presents the empirical data collected from My Ooredoo users, and analyses the results. The transition from theory to empirical investigation represents the progression from understanding what AI *should* do to UX, based on the scholarly literature, to

examining what AI *actually* does to UX, based on the lived experience of real users interacting with a real telecom mobile application in the Algerian market.

CHAPTER II

General Introduction to Chapter II

This chapter establishes the empirical and theoretical foundations required to analyse the impact of artificial intelligence on user experience within the My Ooredoo Algeria mobile application. The investigation revolves around a central question: how does the digital transformation of a mobile network operator in an emerging market reconfigure the customer relationship, and to what extent does the integration of AI in its digital channels reshape the dynamics of satisfaction and loyalty?

Two complementary levels of analysis organize the response. The first concerns Ooredoo Algeria as an organisation its history, its positioning within the Algerian triopolistic mobile market, and the digital transformation trajectory it has pursued since 2019. The second concerns the concrete instruments of that transformation: the My Ooredoo application, the Customer Value Management department, and the Ooredoo Chat conversational agent, examined through the theoretical lenses provided by the literature.

The analysis rests on three pillars. The first is academic: the SERVQUAL, E-S-QUAL, TAM and UTAUT2 frameworks constitute the theoretical backbone, and each is developed with full referencing in the body of the chapter. The second is empirical: primary data drawn from an interview conducted within the Customer Value Management team of Ooredoo Algeria. The third is institutional: ARPCE reports, Ooredoo Group publications and DataReportal provide the sectoral framing throughout.

SECTION 1: OOREDOO ALGERIA AND DIGITAL TRANSFORMATION

1.1 Ooredoo Algeria: Organisational Identity and Strategic Position

1.1.1 General Presentation and Market Position

Ooredoo Algeria is an Algerian telecommunications operator active in a sector that Law No. 18-04 of 10 May 2018 redefined from *télécommunications* to *communications électroniques* a redefinition that brought voice, broadband data and digital value-added services under the supervision of the *Autorité de Régulation de la Poste et des Communications Électroniques* (ARPCE).¹ The company operates under the legal designation Wataniya Télécom Algérie (WTA) S.p.A., with its registered headquarters at 66, Route de Ouled Fayet, Chéraga, 16001 Algiers. A subsidiary of Ooredoo Q.P.S.C., the Qatar-based telecommunications group, it provides mobile voice, SMS and broadband connectivity across the Algerian territory. At the close of Q4 2024, the company served 14,479,676 active mobile subscribers within a national base of 54,050,526 SIM cards a market share of 26.79%.²

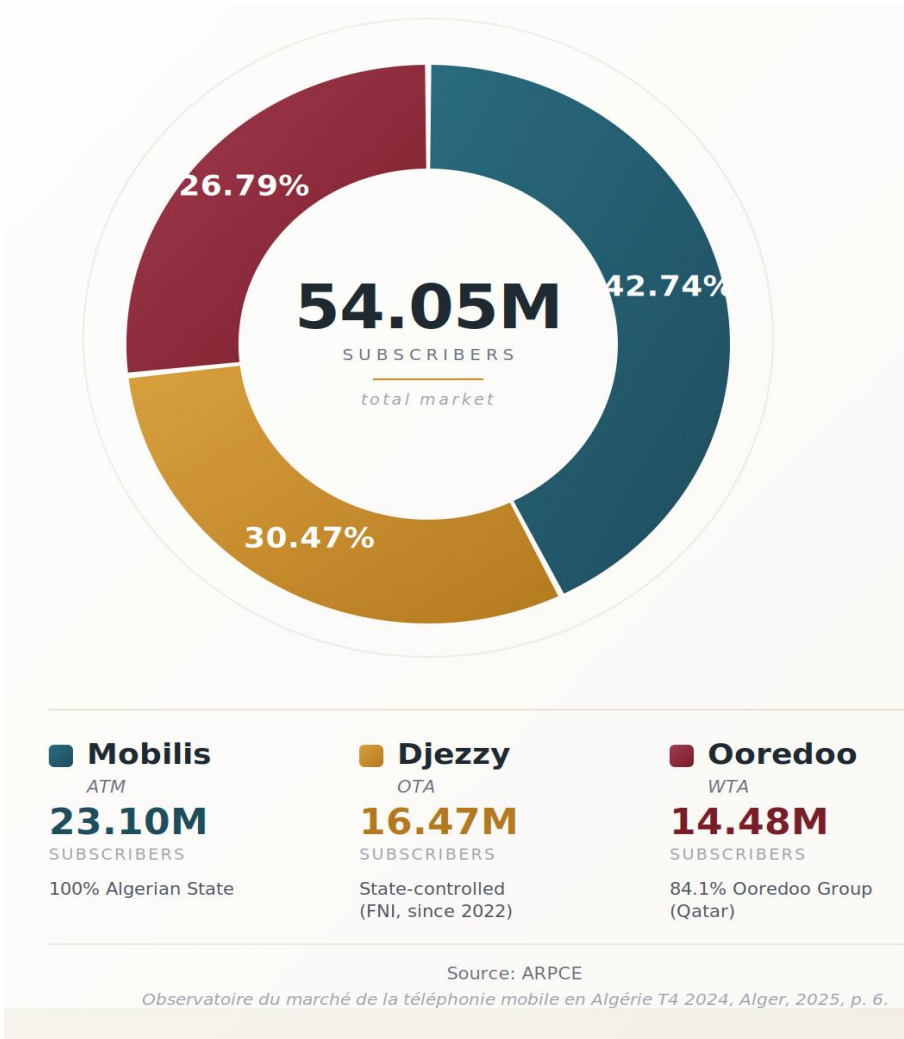
Executive leadership is exercised by Chief Executive Officer Roni Tohme, appointed on 1 August 2023. The marketing direction, headed by Chief Marketing Officer Ahlem Bouzid, oversees the Digital Operational Director and the Customer Value Management (CVM) team the operational centre of AI-driven personalisation examined later in this chapter. Ownership stands at approximately 84.1% Ooredoo Group, with the remainder held by minority and strategic partners. As one of the Group's fastest-growing operating companies (revenue +15%, EBITDA +21% in 2024), the Algerian subsidiary benefits from the Group-wide NVIDIA Cloud Partnership signed in June 2024, which lays the infrastructural foundation for a sovereign AI cloud supporting the operator's data analytics and customer-experience initiatives.³

¹République Algérienne, Loi n° 18-04 du 10 mai 2018 relative aux communications électroniques, *Journal Officiel* n° 27, art. 3.

²ARPCE (2025), *Observatoire du marché de la téléphonie mobile en Algérie T4 2024*, Alger, p. 6.

³BOUZID A. and HAJRI I. (2025), "Leading Algeria's Digital Leap", *Telecom Review Africa*, [online] <https://www.telecomreviewafrica.com> [accessed 03/05/2026].

Figure 25: Algerian Mobile Market Shares, Q4 2024



Source : ARPCE, *Observatoire du marché de la téléphonie mobile en Algérie T4 2024*, Alger, 2025, p. 6.

1.1.2 Historical Evolution and Key Milestones

Ooredoo Algeria traces its origins to the award of Algeria's third GSM licence on 2 December 2003 to Wataniya Telecom Algérie, a consortium led by Wataniya Telecom Kuwait. Commercial operations began in August 2004 under the brand name *Nedjma* Arabic for *star* accompanied by the launch of Algeria's first EDGE network. Qtel (later Ooredoo) acquired a controlling 51% stake in Wataniya Telecom in March 2007 for USD 3.8 billion, subsequently raising this to 91.2% by October 2012.

The company's trajectory unfolds across five distinct phases. During the *implantation phase* (2004–2012), Nedjma built rapid national coverage and cultivated a loyal young urban subscriber base, reinforced by its sponsorship of the Algerian national football team. The

rebranding phase (2013) produced the formal transition to Ooredoo Algeria on 21 November 2013, aligned with the parent group's global rebranding from Qtel to Ooredoo, and was accompanied by the commercial launch of 3G services in December 2013. The *technological leadership phase* (2016–2019) was anchored by the commercial launch of 4G in September 2016 the first operator to do so in Algeria subsequently extended to all 58 *wilayas*. The *digital transformation phase* (2019–2024) opened with the arrival of Mathias Hanel as Chief Commercial Officer in October 2019 and established AI, the My Ooredoo application and digitised customer journeys as strategic levers.¹ The *5G phase* (2025–2026) is marked by the award of a 5G licence in July 2025 for DZD 21 billion, a commercial launch on 4 December 2025, and the extension of 5G coverage to all 58 *wilayas* by March 2026 making Ooredoo the first Algerian operator to achieve nationwide 5G presence.²

Figure 26: Ooredoo Algeria: Key Milestones



1.1.3 Organisational Structure

The organisational structure of Ooredoo Algeria reflects conventional telecommunications-industry functional groupings articulated around four complementary

¹HANEL M. (2021), "Ooredoo Algeria: The Mobile Operator's Journey to Success", *Telco Magazine*, [online] <https://telcomagazine.com> [accessed 03/05/2026].

²Ooredoo Algérie (2026), "Ooredoo Algérie étend son réseau 5G sur toutes les wilayas", [online] <https://www.ooredoo.dz> [accessed 04/05/2026].

domains. Network Operations and Technology Management covers radio access networks (2G through 5G), transport infrastructure and core network systems. Commercial and Marketing Operations encompasses prepaid and postpaid offerings, brand communication and the customer-experience agenda. Customer Value Management and Analytics the operational heart of the AI deployment examined later in this chapter runs the machine learning and prediction models that support churn prevention, Next-Best-Offer determination, multi-SIM detection and geolocation-based marketing. Digital Channel Management oversees the development and continuous enhancement of the My Ooredoo application and the operator's web portal.

The company employs approximately 4,500 staff at its headquarters in Chéraga, supported by a national distribution network of around 250 points of sale, 20 franchise shops and six digital flagship stores. The CEO, in an interview with *Telecom Review Africa*, summarised the company's strategic DNA as a story of *"vision, resilience, and continuous innovation"*, underscoring that AI was *"already being deployed across several layers of our operations from smart customer support systems to predictive analytics that optimize network performance and anticipate customer needs."*¹

1.1.4 The Service Quality Journey

Over two decades, Ooredoo Algeria's service quality trajectory has traversed three phases: basic GSM call quality (2004–2012), 3G/4G data quality (2013–2020), and digital experience quality (2020 to present). Independent validation of the third phase is provided by the Opensignal Mobile Network Experience Report of April 2025², which ranked Ooredoo Algeria first in download speed experience at 13.8 Mbit/s 69.7% faster than Mobilis and more than twice the speed of Djezzy as well as first in upload speed experience (5.8 Mbit/s) and video experience (46.2/100).

Mapped onto the SERVQUAL dimensions that Henniche (2019)³ validated empirically in the Algerian telecom context, this trajectory manifests as follows: *tangibles* (Espaces Ooredoo smart stores, rural site deployment under the Universal Telecommunications Service programme); *reliability* (Opensignal Core Consistent Quality recognition); *responsiveness* (333/330 call centres, Ooredoo Chat virtual agent); *assurance* (regulatory compliance, data

¹TOHME R. (2024), "Ooredoo Algeria: Powering Algeria's Digital Future", *Telecom Review Africa*, [online] <https://www.telecomreviewafrica.com> [accessed 03/05/2026].

²Opensignal (2025), *Algeria Mobile Network Experience Report*, April 2025, p. 8.

³HENNICHE N., op. cit., p. 92.

protection certifications); and *empathy* (Splio-driven individual-level personalisation, Noudjoum customised rewards). These five dimensions will serve as evaluative anchors in the empirical analysis of Chapter II.

1.2 Ooredoo as a Digital Actor

1.2.1 Overview of the Algerian Digital Sector

Algeria's digital economy displays sustained growth. According to DataReportal's *Digital 2025: Algeria* report¹, the country records 36.2 million internet users (penetration: 76.9%, up from 72.9%), 54.8 million cellular mobile connections (116% of the population) and 25.6 million active social media users (54.2%), distributed principally across Facebook, TikTok, YouTube and Instagram. The ITU ICT Development Index 2025 ranked Algeria 74th globally with a score of 86.1/100 a 15-place improvement over the prior year. At the policy level, the *Stratégie Nationale de Transformation Numérique* "Pour une Algérie Numérique 2030", unveiled on 12 May 2025, and the National AI Strategy adopted in December 2024 frame mobile network operators as gatekeepers of digital inclusion.

1.2.2 Digitalisation Initiatives and Digital Ecosystem

Ooredoo Algeria has positioned digital transformation at the core of its corporate strategy a shift its leadership describes as an evolution from traditional connectivity provider toward comprehensive digital lifestyle brand. On the infrastructure side, the Nokia framework agreement (MWC 2023) deploys the AirScale portfolio with Massive MIMO adaptive antennas, raising Nokia's share of the Algerian RAN to approximately 50%; the Huawei agreement (MWC 2024) mandates full migration of core networks to a 5G service-based architecture; and NEC next-generation firewalls deployed in March 2026 complete the security layer. On the software side, the Infobip Anam Protect SMS firewall, which uses embedded machine learning for fraud detection, reported traffic growth of 15% and revenue improvement of 35% post-deployment.

The resulting digital ecosystem orchestrates six interconnected components: the My Ooredoo mobile application (the primary customer touchpoint), the my.ooredoo.dz web portal, the Ooredoo Chat virtual agent (powered by Sprinklr, 24/7 conversational support), the Splio Individuation® platform (operational since 2020, orchestrating AI-driven personalisation

¹DataReportal, op. cit., p. 18.

across channels), the Noudjoum loyalty programme accessible via the application, and the operator's social media presences Facebook (6.3 million followers), Instagram, TikTok and X.¹

1.2.3 Competitive Positioning and Service Quality Maturity

Within Algeria's triopolistic mobile market, competitive dynamics turn on the tension between subscriber scale and digital service differentiation. Mobilis leverages its state affiliation and universal service mandate to command 42.74% of subscriptions, but its 5G deployment lagged behind Ooredoo at the December 2025 launch. Djezzy, state-controlled through the *Fonds National d'Investissement* since VEON's exit in August 2022, competes primarily on pricing and urban coverage. Ooredoo, the only foreign-controlled operator, differentiates through operational efficiency ($\approx 42\%$ EBITDA margin), network performance leadership and digital experience innovation.² All three operators paid a combined DZD 63.9 billion for their 5G licences in November 2025; Ooredoo was the first to extend 5G coverage to all 58 *wilayas* by March 2026, operating a contiguous 100 MHz channel in the 3.5 GHz (n78) band.³

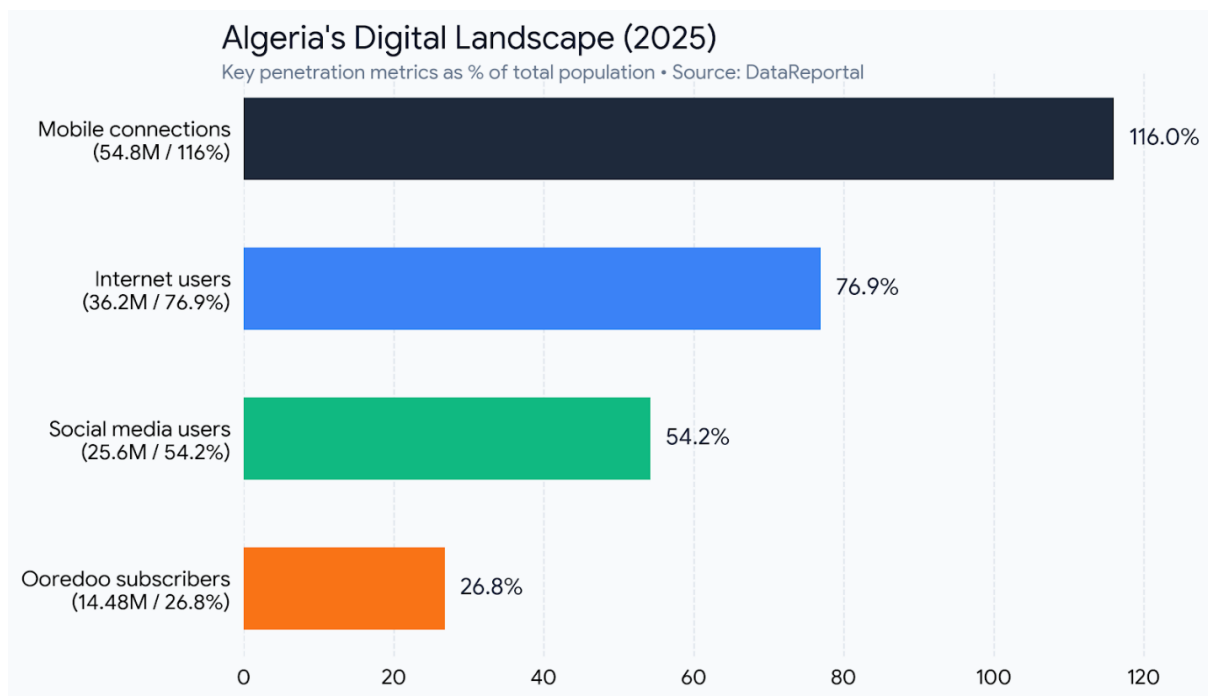
Mapped onto a four-level service quality maturity model (Reactive $\rightarrow$ Multichannel $\rightarrow$ Omnichannel $\rightarrow$ Intelligent Omnichannel), Ooredoo Algeria currently sits between Levels 3 and 4. Its Ooredoo Chat remains a hybrid rule-based/ML agent on Sprinklr, one generation behind the Group benchmark Obot at Ooredoo Qatar, built on GPT-4o with a Retrieval-Augmented Generation architecture within Microsoft Azure AI Foundry and reported to reduce average handling time from 7 to 5 minutes.⁴ App-store ratings reflect this positioning: My Ooredoo Algeria scores 3.7/5 on Google Play ($\approx 40,100$ reviews, 5 million+ downloads) but only 2.4/5 on the App Store (212 reviews), with recurring complaints about authentication failures, payment errors and interface inconsistencies. The gap between the sophistication of the back-end AI infrastructure and the unevenness of the front-end user experience constitutes the central analytical tension of this thesis.

¹Ooredoo Algérie, internal data and official social media presences, 2025.

²Ooredoo Group, consolidated financial reports 2024; ARPCE, *Observatoire*, op. cit., p. 6.

³ARPCE, 5G licence allocation decision, November 2025; Ooredoo Algérie, 5G coverage communiqué, March 2026.

⁴Ooredoo Qatar (2025), "Ooredoo Showcased Obot at Web Summit Qatar 2025", [online] <https://www.ooredoo.qa> [accessed 03/05/2026].

Figure 27: Algeria's Digital Landscape, 2025 (DataReportal)

Source: DataReportal, *Digital 2025: Algeria* (Data via Kepios & GSMA Intelligence).

1.3 Ooredoo's Digitalisation Strategy

1.3.1 Internal Digitalisation

Internal digitalisation at Ooredoo Algeria encompasses the modernisation of network infrastructure and information systems. On the network side, the Nokia AirScale rollout under the MWC 2023 framework agreement brings multi-band radios and Massive MIMO adaptive antennas; the Huawei MWC 2024 agreement mandates full migration of all core networks to a 5G service-based architecture; ZTE supplies the dual-band 3.5 GHz AAUs for 5G RAN, deployed for the December 2025 commercial launch; and NEC next-generation firewalls were activated in March 2026.

On the information systems side, Ooredoo has modernised its CRM, business intelligence and enterprise data architecture to produce a unified analytical infrastructure. Real-time performance dashboards give decision-makers simultaneous visibility over network KPIs, commercial results and customer satisfaction indicators. The automation of back-office processes billing reconciliation, inventory management, vendor settlements has freed human capital for higher-value analytical and customer-facing activities.

1.3.2 External Digitalisation

External digitalisation refers to the migration of customer interactions from physical and voice channels toward digital self-service platforms. The cornerstone of this effort is the Splio Individuation® partnership, operational since 2020. Unlike traditional rule-based campaign-management systems that broadcast messages to predefined segments, Individuation operates at the level of the individual subscriber, arbitrating for each customer, on a daily basis the most relevant message, the most appropriate channel (SMS, in-app push notification, web banner, USSD or call-centre outbound contact) and the optimal moment of delivery, based on a continuously refreshed behavioural profile.¹

After five years of collaboration, Splio publicly documented the outcomes: customer-marketing-generated revenue doubled, satisfaction and loyalty indicators improved, and marketing-team productivity was optimised.² Hichem Abdelhak, VP Telecom at Splio, characterised the transformation thus: *"the operator is now able to anticipate and personalise each customer's needs to maximise their loyalty."* The framework of Meuter et al. (2000)³ provides the academic counterpart: self-service technologies generate satisfaction when they solve an intensified need or perform better than the human alternative, and generate acute dissatisfaction when they fail through technology malfunction, process breakdown or poor design.

1.3.3 Digital Channel Strategy

The digital channel strategy is anchored by the My Ooredoo super-app as the central hub, complemented by the my.ooredoo.dz web portal, the Ooredoo Chat virtual agent, and social media presences. Assisted channels 333 (B2C) and 330 (B2B) call centres, USSD codes such as *222# remain available for complex enquiries and subscribers with limited digital literacy. The physical estate of 250+ points of sale and 51 *Espaces Ooredoo* maintains territorial capillarity and serves as the mandatory point of identity verification for operations requiring physical SIM handling. The strategy emphasises channel convergence rather than substitution: actively promoting digital volumes while maintaining physical presence as a safety net a duality dictated by the Algerian market reality of 95.66% prepaid penetration, uneven digital literacy

¹Splio, technical documentation and commercial presentation of the Individuation® platform, 2020–2025.

²Splio (2025), "Ooredoo Algeria and Splio: 5 Years of Marketing Innovation", press release, MWC Barcelona, 4 March 2025.

³MEUTER M.L. et al. (2000), "Self-Service Technologies: Understanding Customer Satisfaction with Technology-Based Service Encounters", *Journal of Marketing*, Vol. 64, No. 3, pp. 50–64.

by age and geography, and a consumer base ranging from digital-native youth to elderly subscriber's dependent on physical retail.

1.3.4 Service Quality Strategy

The service quality strategy cascades ARPCE QoS obligations into channel-level service-level agreements and KPIs: chatbot first-contact-resolution rate, push-notification click-through and opt-out rates, application uptime, payment success rate (SATIM-CIB / BaridiNet-Edahabia), Net Promoter Score by channel and time-to-resolution. This approach is theoretically anchored in Sousa and Voss's (2006) framework on multichannel service quality, which demonstrates that cross-channel consistency is at least as important as the performance of any individual channel a single friction point can degrade the global perception of quality even where network performance is objectively strong.

1.4 The My Ooredoo Application

1.4.1 Presentation

The My Ooredoo application is the principal digital interface between Ooredoo Algeria and its subscriber base, and the most visible manifestation of its digital transformation strategy. Distributed via Google Play (package identifier: com.algeria.selfcare.app.android), the Apple App Store (ID: 1644340373) and Huawei AppGallery (ID: C107690933), the application is available in French, Arabic and English, reflecting the trilingual character of the Algerian market. It has accumulated more than five million Android installations.

Its functional architecture spans five domains. *Account management and consumption monitoring* provides real-time tracking of voice, SMS and data usage, biometric authentication, invoice access and multi-line management. *Recharging and payment* integrate the traditional scratch-card mechanism, electronic payment via CIB card (through the SATIM interbank processor) and Edahabia card (through BaridiNet), and the eStorm platform. *Offer and bundle management* encompasses the NYOOZ personalised bundle builder, which lets subscribers compose a tailored prepaid plan by selecting data volumes, voice minutes, SMS quantities, validity period and modular extras (WhatsApp, YouTube, Instagram, TikTok or Snapchat passes). *Customer service and assistance* provide access to the Ooredoo Chat agent. *Loyalty and engagement* surface the Noudjoum programme one point per DZD 25 recharged, with progressive bonuses at cumulative thresholds of DZD 250, 1,250 and 3,750 and 5G activation directly within the app, without requiring physical SIM replacement for eligible subscribers.

1.4.2 Evolution

The application's evolution traces the operator's broader digital transformation. The legacy Android package (dz.ooredoo.myooredoo) reached its final version (1.46.1) in May 2021 before a complete re-platforming in 2023 under the current package identifier. Subsequent releases reflect strategic priorities: v1.2.1 (March 2024) introduced YOOZ eligibility; v1.2.6 (June 2024) integrated DIMA+; v1.4.2 (March 2025) delivered a comprehensive interface redesign; v1.4.8 (September 2025) added dark mode and the gift-a-bundle feature; v1.5.4 (February 2026) introduced a Ramadan-themed UI. This progression describes a classic super-app maturation curve from a balance-checking utility toward a personalised digital lifestyle platform integrating transactional services, gamified loyalty and AI-driven personalisation.

1.4.3 Limitations and Challenges

Despite its functional breadth, the application confronts several structural constraints inherent to the Algerian market. On the payments side, the SATIM interbank processor requires CIB cardholders to obtain an online password physically at their bank branch a friction point that no amount of UX design can eliminate. Foreign payment instruments (Visa, Mastercard, Apple Pay, Google Pay, PayPal) are not accepted, a direct consequence of the Algerian dinar's non-convertibility. Ooredoo Algeria does not currently hold a Payment Service Provider (PSP) licence under Bank of Algeria Instruction No. 06-2025 of 17 August 2025¹, which would require approximately DZD 160 million in minimum capital and a dedicated on-shore entity a configuration that precludes a proprietary mobile-money wallet.

On the accessibility side, uneven digital literacy particularly among older demographics and rural populations constrains adoption outside urban centres. The prepaid market dominance (95.66% of subscribers) reduces the incentive to create a digital account among low-frequency users. Security measures, including the blocking of the application on rooted Android devices, generate additional friction reported in user reviews. Google Play and App Store reviews (2023–2025) document recurring themes: authentication failures, payment errors during CIB or Edahabia transactions, slow loading on lower-end Android devices, forced updates interrupting the user experience, and opacity in personalised offer presentation.

¹Banque d'Algérie, Instruction n° 06-2025 du 17 août 2025 relative aux prestataires de services de paiement.

1.4.4 Customer Experience Metrics

The performance of My Ooredoo is evaluated through a composite set of indicators. Public proxies 3.7/5 on Google Play and 2.4/5 on the App Store constitute sentiment signals biased toward extreme experiences but revealing of recurring friction themes. Internal metrics include monthly active users (MAU), session duration, task completion rate, crash-free session percentage, NPS, CSAT and Customer Effort Score (CES) by channel.

Mapped onto M-S-QUAL (Huang, Lin and Fan, 2015)¹, the user review evidence translates as follows: payment friction signals a *fulfillment* failure; OTP delays signal a *responsiveness* failure; login crashes signal a *system availability* failure; and opaque personalisation signals a *privacy* concern.

1.5 Digitalization of Customer Interactions

1.5.1 Main Digitalised Customer Journeys

Ooredoo Algeria has systematically mapped and digitised its high-frequency customer journeys. The *recharge journey* supports one-click top-up via scratch card or electronic payment in under a minute. *Plan management* migration between prepaid bundles, activation of roaming packages, modification of favourite numbers no longer requires any store visit. *Consumption monitoring and invoice access* operates 24 hours a day within the application. The *5G activation journey* represents the most complete example of end-to-end digitalisation: eligible subscribers move from checking eligibility to activating 5G service entirely within the application. The *loyalty redemption journey* allows Noudjoum members to consult point balances and redeem rewards without human intermediation.

1.5.2 Contribution to the Digital Experience

The digitalisation of customer interactions contributes to service quality along three dimensions: it extends accessibility beyond retail hours, removes geographic constraints, and generates structured behavioural data that continuously enriches predictive models. The canonical Group benchmark is provided by Ooredoo Kuwait's Dialpad deployment, where digital inbound interactions rose from 0.4% to 34–37% of monthly volume following the integration of WhatsApp, Facebook Messenger, Twitter DM and Instagram DM. The Digital Channel Director, Raffi Tokmakjian, observed that "*a single digital agent can serve up to 4*

¹HUANG M.-H., LIN Y.-H. and FAN Y.-C. (2015), "M-S-QUAL: Mobile Service Quality Measurement", *Journal of Business Research*, Vol. 68, No. 6, pp. 1185–1196.

interactions comfortably vs. a call center that can only handle 1 call at a time" compressing wait times and reducing service costs simultaneously.

Meuter et al.'s (2000)¹ framework on self-service technologies supplies the theoretical counterpart: SSTs produce satisfaction when they solve an intensified need, perform better than the available alternative, or function as an autonomy-enhancing resource; they generate acute dissatisfaction when they fail through technology malfunction, process breakdown or poor design. These three failure modes map precisely onto the recurring complaints documented in My Ooredoo's user reviews.

1.5.3 Loyalty Integration

The Noudjoum loyalty programme is deeply embedded within Ooredoo Algeria's digital interaction framework, converting routine transactions into relationship-building opportunities. Theoretically, this mechanic aligns with Oliver's (1999)² four-stage loyalty progression: the *cognitive* layer (quality beliefs, offer relevance) is fed by Splio-driven personalisation; the *affective* layer (emotional attachment, brand preference) is reinforced by points accumulation and tier recognition; the *conative* layer (behavioural intention, commitment) is expressed through exclusive digital offers and bundle subscriptions; and the *action* layer (repeat purchase, resistance to competitive overtures) is the ultimate outcome targeted by CVM interventions.

Empirically, app-engaged telecom customers exhibit churn rates two to three times lower than non-app customers a pattern consistent with the doubling of CRM-generated revenue documented by Splio after five years of partnership.³ Reichheld and Sasser (1990)⁴ established the foundational economic logic: a 5% reduction in the defection rate can increase profits by 25% to 95% across service industries. It is precisely this mechanism that the CVM department of Ooredoo Algeria seeks to activate through its six production ML models.

1.6 Artificial Intelligence in My Ooredoo

1.6.1 Overall AI Integration

Artificial intelligence at Ooredoo Algeria operates on two distinct but complementary pillars. The first, visible to the user, is the Ooredoo Chat conversational agent. The second,

¹MEUTER M.L. et al., op. cit., p. 53.

²OLIVER R.L. (1999), "Whence Consumer Loyalty?", *Journal of Marketing*, Vol. 63, pp. 33–44.

³Splio, op. cit.

⁴REICHHELD F.F. and SASSER W.E. (1990), "Zero Defections: Quality Comes to Services", *Harvard Business Review*, Vol. 68, No. 5, pp. 105–111.

invisible but analytically more powerful, is the Customer Value Management stack driven by Splio and the internal data science teams. The distinction between visible AI and invisible AI, formalised by Bock, Wolter and Ferrell (2020)¹, is analytically productive: it permits separate examination of what the user directly perceives and what operates backstage to shape the offers they receive. Strategically, this deployment is anchored in the NVIDIA Cloud Partnership (June 2024) and in the RISE strategy's emphasis on *"best-in-class capabilities in data science, AI, customer value management and operational excellence."*²

1.6.2 The Chatbot Module: Ooredoo Chat

Ooredoo Chat is a hybrid virtual agent built on the Sprinklr conversational platform, combining rule-based dialogue management with machine-learning-based intent recognition. It is accessible via the Services menu in the application and on the institutional website at ooredoo.dz, greeting users in French and Arabic. The agent handles frequently asked questions on tariffs, subscription procedures and service-termination modalities, and escalates complex cases to human advisors. In its current state, it operates as a closed-domain, task-oriented, hybrid rule-based/ML system the classification proposed by Adamopoulou and Moussiades (2020)³ rather than as a generative large-language-model interface.

The Group benchmark is Obot, unveiled by Ooredoo Qatar at Web Summit Qatar 2025.⁴ Built on GPT-4o with Retrieval-Augmented Generation (RAG) over an internal knowledge base, integrated with Microsoft Dynamics 365 Omnichannel and Azure AI Foundry, Obot operates across the web, application, WhatsApp, Facebook and X, and was extended in November 2025 with real-time voice capabilities and an AI-generated avatar interface. Industry sources cite an average-handling-time reduction from 7 to 5 minutes. The maturity gap between Algiers and Doha is real and strategically acknowledged; it constitutes one of the drivers of the research hypotheses tested in Chapter II.

¹BOCK D.E., WOLTER J.S. and FERRELL O.C. (2020), "Artificial Intelligence: Disrupting What We Know About Services", *Journal of Services Marketing*, Vol. 34, No. 3, pp. 317–334.

²Ooredoo Group (2025), *Capital Markets Day 2025 RISE Strategy Presentation*, Doha, 3 November 2025.

³ADAMOPOULOU E. and MOUSSIADES L. (2020), "Chatbots: History, Technology, and Applications", *Machine Learning with Applications*, Vol. 2, art. 100006.

⁴Ooredoo Qatar, op. cit.

A critical academic caveat applies to the chatbot disclosure dimension. Luo et al. (2019)¹, in a field experiment covering more than 6,200 customers, demonstrated that disclosed AI chatbots can reduce purchase rates by up to 79.7% compared with undisclosed ones, owing to perceived lower competence and empathy. This finding acquires regulatory weight under Law No. 25-11 of July 2025², which introduces mandatory transparency requirements for automated processing of personal data adding a compliance dimension to what is already a UX challenge.

1.6.3 Customer Value Management: Architecture and Models

The CVM department of Ooredoo Algeria constitutes the analytical engine of the operator's customer relationship strategy. It is structured as three coordinated sub-teams: an IT team that maintains the data infrastructure and integration layer; a Machine Learning team that designs, trains and validates predictive models; and an AI/Analytics team that conducts segmentation research, scenario modelling and the interpretation of model outputs for commercial teams.³

The foundational logic of CVM deserves explicit articulation. Without CVM, all subscribers receive the same default product offering regardless of age, geography, profession or usage behaviour. A 20-year-old student who uses mobile internet primarily for gaming and a 65-year-old professional who makes principally voice calls see the same commercial proposition. CVM exists to correct precisely this indifferentiation: by analysing subscriber behaviour across multiple criteria geographic region, profession, age bracket, consumption type and volume, recharge patterns, application preferences it allows the delivery of a service calibrated to each individual's real profile. As the CVM team explained in interview:⁴ *"We detect a student during exam period and offer them YouTube or internet services to help them revise and focus on their studies whether at lycée or university level. That's what CVM is, in essence."*

Six families of machine learning models are currently in production.⁵

¹LUO X. et al. (2019), "Frontiers: Machines vs. Humans: The Impact of AI Chatbot Disclosure on Customer Purchases", *Marketing Science*, Vol. 38, No. 6, pp. 937–947.

²République Algérienne, Loi n° 25-11 du 24 juillet 2025 relative à la protection des données à caractère personnel, *Journal Officiel*.

³Internal interview, op. cit.

⁴Idem.

⁵Idem.

The *churn prediction model* identifies subscribers at risk of porting their number to Mobilis or Djezzy. It detects behavioural signals statistically associated with subsequent attrition declining recharge frequency, reduced application engagement, falling data consumption and triggers personalised retention interventions calibrated to the inferred value profile of the at-risk subscriber. Gradient boosting methods, and XGBoost in particular, display superior performance on telecom churn datasets (Ahmad, Jafar and Aljoumaa, 2019¹; Sikri et al., 2024²).

The *bundle determination model* combines manual market analysis with automatic ML scoring to identify the optimal bundle for each subscriber at any given moment. Its outputs feed targeted SMS campaigns and in-app push notifications, coordinated with the application team for deployment.

The *Next-Best-Offer (NBO) model* predicts the optimal product or service to present to the subscriber at their next interaction, based on consumption history, declared preferences and the current offer portfolio.

The *Next-Best-Action (NBA) model* goes one step further: rather than predicting the optimal product, it predicts the optimal marketing action retention, upsell, cross-sell, activation, reactivation to maximise the long-term value of the subscriber relationship.

The *multi-SIM detection model* identifies subscribers who simultaneously hold an Ooredoo SIM and a competitor SIM, by analysing statistical consumption patterns volume, regularity, periodicity that are inconsistent with Ooredoo being the subscriber's sole active line. Detected multi-SIM subscribers are prioritised for share-of-wallet consolidation campaigns.

The *satisfaction prediction model* infers, from behavioural signals, the probability that a subscriber is experiencing service degradation without having formally complained enabling proactive intervention before dissatisfaction converts into churn.

All model inputs include geolocation data, consumption type and volume, purchase history, ARPU trajectory, and complaint interaction logs. Model outputs are delivered via SMS, push notifications and in-app surfacing through the *Forfaits Exclusifs* tile, in coordination with

¹AHMAD R., JAFAR A. and ALJOUmaa K. (2019), "Customer Churn Prediction in Telecom using Machine Learning", *Journal of Big Data*, Vol. 6, No. 1, art. 28.

²SIKRI S. et al. (2024), "A Comprehensive Review of Churn Prediction Models in Telecom", *IEEE Access*, Vol. 12, pp. 45678–45699.

the application development team. The Splio Individuation® platform orchestrates the daily message-channel arbitration at the individual subscriber level, ensuring that each customer receives the most relevant communication through the most appropriate channel at the optimal moment.¹

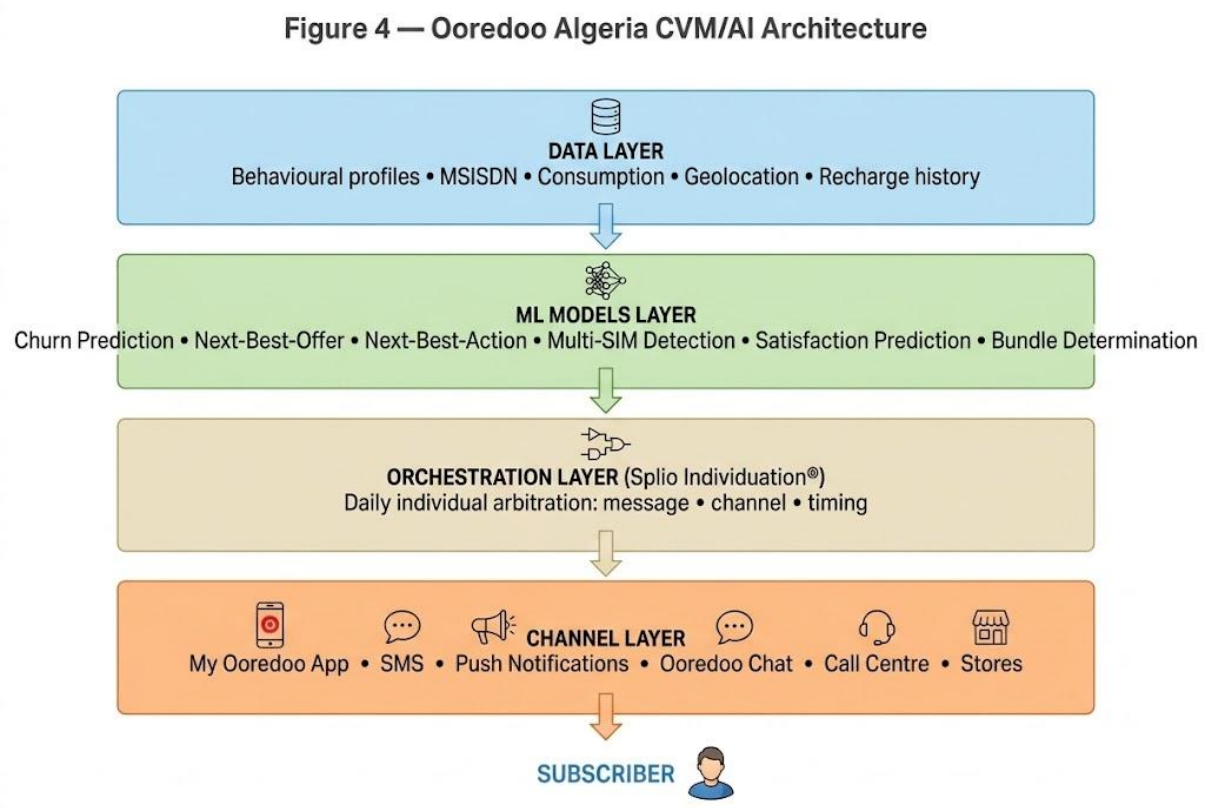


Figure 28: Ooredoo Algeria CVM/AI Architecture

Source: Author’s synthesis based on the interview conducted with the Ooredoo Algeria Customer Value Management (CVM) team.

1.6.4 Impact on Service Quality and Loyalty

Mapped onto the AI intelligence taxonomy of Huang and Rust (2021)² distinguishing *mechanical AI* (standardisation), *thinking AI* (personalisation) and *feeling AI* (relationalisation), the CVM deployment operates primarily in the registers of mechanical AI (automation of campaign execution and bundle determination) and thinking AI (NBO/NBA personalisation and churn prediction). The feeling-AI register empathic chatbots, sentiment-aware escalation,

¹Splio, op. cit.
²HUANG M.-H. and RUST R.T. (2021), "A Strategic Framework for Artificial Intelligence in Marketing", *Journal of the Academy of Marketing Science*, Vol. 49, No. 1, pp. 30–50.

proactive satisfaction management remains nascent in the Algerian deployment, with the satisfaction prediction model representing an early step in this direction.

The infusion of AI into the customer management system generates measurable impacts across the service quality and loyalty chain. Mechanical AI enhances the E-S-QUAL dimensions of efficiency and system availability by automating previously manual processes. Thinking AI drives personalisation: Chandra et al. (2022)¹, reviewing 383 publications on personalised marketing, find that personalisation reduces customer cognitive fatigue and enhances engagement and satisfaction with the personalisation–privacy paradox emerging as a critical boundary condition. Feeling AI, still nascent in Algeria, addresses the SERVQUAL responsiveness and assurance dimensions by making customers feel individually understood rather than mass-addressed.

The causal chain connecting these AI pillars to loyalty outcomes runs as follows: AI-driven personalisation generates perceived value and relevance (cognitive loyalty); perceived value produces satisfaction (affective loyalty); satisfaction engenders continuance intention (conative loyalty); conative loyalty produces repeat usage and resistance to competitive offers (action loyalty). At Ooredoo Oman, a sister operation that has deployed Splio Individuation® since 2022, this chain produced a documented 19% increase in incremental revenue and a 20% improvement in retention over three years a benchmark the Algerian CVM team cites as indicative of what is attainable.

1.6.5 Customer Intelligence in My Ooredoo

The My Ooredoo application constitutes a rich source of customer intelligence, capturing behavioural signals that feed continuous service quality improvement. The data types collected include consumption patterns (voice, SMS and data volumes; preferred applications), geolocation, payment behaviour (methods used, frequency, amounts), in-app interaction patterns (screens visited, abandonment points, session duration), satisfaction signals (post-interaction CSAT, NPS surveys) and churn indicators (top-up gaps, declining engagement, port-out enquiries).²

¹CHANDRA S. et al. (2022), "Personalization in Personalized Marketing: Trends and Ways Forward", *Psychology & Marketing*, Vol. 39, No. 8, pp. 1529–1562.

²Internal interview, op. cit.

The processing pipeline follows the analytical maturity model of Davenport and Harris (2007)¹: descriptive analytics (what happened?) → predictive analytics (what will happen?) → prescriptive analytics (what should be done?). At Ooredoo Algeria, this translates into data collection → feature engineering → ML modelling (the six CVM models described above) → campaign activation through Splio Individuation® → outcome measurement (uplift versus control group, ARPU delta, churn delta) → feedback loop into model retraining. This closed-loop architecture is precisely the design that Huang and Rust (2021)² prescribe for achieving thinking-AI maturity in marketing: chatbot interaction logs enrich CVM models, which generate personalised offers delivered via the application, the outcomes of which feed back into model optimisation.

For customer intelligence and one-to-one marketing strategy, Peppers and Rogers (2022)³ provide the foundational framework: the deeper the knowledge of the individual customer, the more relevant the value proposition that can be constructed. Law No. 25-11 of July 2025 constrains precisely this equation by imposing consent, purpose limitation and data minimisation requirements. The tension between personalisation depth and regulatory compliance between more data enabling better NBO/NBA recommendations and legal obligations requiring minimal data collection constitutes the central operational trade-off of AI-driven CVM, and one of the operative challenges that the empirical investigation of Chapter II will seek to illuminate from the user's perspective.

1.7 Omnichannel Strategy and Future Directions

Verhoef, Kannan and Inman (2015)⁴ define omnichannel retail management as the synergetic orchestration of all available channels and customer touchpoints so that experience and performance are jointly optimised. Ooredoo Algeria's architecture pursues this ideal across four layers digital self-service (My Ooredoo application, web portal, WhatsApp support, social media), assisted-remote (333/330 call centres, IVR, USSD), physical presence (250+ points of sale, 20 franchise shops, six digital flagship stores), and an AI/CVM orchestration layer operating horizontally across the three preceding layers and keyed to the MSISDN as the unified

¹DAVENPORT T.H. and HARRIS J.G. (2007), *Competing on Analytics: The New Science of Winning*, Harvard Business School Press, Boston, p. 7.

²HUANG M.-H. and RUST R.T., op. cit., p. 35.

³PEPPERS D. and ROGERS M. (2022), *Managing Customer Experience and Relationships*, 4th ed., Wiley, Hoboken, p. 43.

⁴VERHOEF P.C., KANNAN P.K. and INMAN J.J. (2015), "From Multi-Channel Retailing to Omni-Channel Retailing", *Journal of Retailing*, Vol. 91, No. 2, pp. 174–181.

customer identifier. Within this architecture, the My Ooredoo application occupies a structurally privileged position: it is at once a transactional channel and a data-collection interface that continuously enriches the AI models operating in the background.

Three strategic axes define the forward trajectory. The first is 5G densification and use-case monetisation the nationwide coverage achieved in March 2026 provides the technical foundation for premium enterprise services (smart cities, industrial automation, connected health) and immersive consumer experiences; as the marketing leadership has noted, *"at Ooredoo Algeria, we view 5G not merely as the next step in mobile technology, but as a true catalyst for digital transformation across the nation."*¹ The second is the potential evolution toward a super-app integrating financial services: Bank of Algeria Instruction No. 06-2025² creates a regulatory pathway for Ooredoo Algeria to file a PSP licence application and replicate the *walletii by Ooredoo* model already operational in Oman. The third is the maturation of conversational AI upgrading Ooredoo Chat from a rule-based/ML system toward a generative architecture comparable to Obot Qatar, supported by the Group's NVIDIA sovereign cloud infrastructure and aligned with the National AI Strategy announced in December 2024.

1.8 Regulatory and Compliance Framework

1.8.1 ARPCE Regulations

The Algerian regulatory landscape for telecommunications and data protection has accumulated several layers of legislation. Law No. 2000-03 of 5 August 2000 created the sector regulator. Law No. 18-04 of 10 May 2018 redefined electronic communications and established ARPCE.³ Law No. 18-05 of 10 May 2018 governs e-commerce. Law No. 18-07 of 10 June 2018⁴ established the framework for personal data protection and created the ANPDP (*Autorité Nationale de Protection des Données à Caractère Personnel*), operational since August 2022.

This framework was significantly tightened by Law No. 25-11 of 24 July 2025.⁵ The amendments introduce four major obligations for large-scale data processors: mandatory appointment of a Data Protection Officer (DPO); maintenance of a register of automated processing operations; mandatory Data Protection Impact Assessments (DPIAs) for high-risk

¹Ooredoo Algérie, marketing leadership declaration, 2025.

²Banque d'Algérie, op. cit.

³République Algérienne, Loi n° 18-04, op. cit.

⁴République Algérienne, Loi n° 18-07 du 10 juin 2018 relative à la protection des données à caractère personnel, *Journal Officiel* n° 34.

⁵République Algérienne, Loi n° 25-11, op. cit.

processing; and a five-day breach-notification window to the ANPDP. Penalties range from DZD 20,000 to 1,000,000 per infringement, with criminal sanctions of two months to five years' imprisonment a severity absent from EU GDPR, which relies exclusively on financial penalties.

1.8.2 Service Quality Obligations

Service quality obligations under ARPCE jurisdiction extend beyond aggregate network statistics to geographic equity and consumer redress. Operators must ensure continuous coverage along strategic transportation corridors including the East–West Highway and major north–south national roads. The regulator's enforcement capacity was demonstrated concretely on 23 October 2024, when ARPCE imposed a total fine of DZD 1,053,325,166.30 on the three mobile network operators following a nationwide QoS audit, including DZD 249,496,481.75 on Ooredoo Algeria. The ARPCE communiqué stated that *"certain coverage and quality-of-service requirements remain unmet"*, reaffirming that licence holders must respect their *cahier des charges* under penalty of sanctions reaching up to five percent of annual turnover or partial licence suspension.¹ The operator responded by accelerating the Universal Telecommunications Service rural rollout targeting more than 1,200 new sites in partnership with Algérie Télécom and densifying urban infrastructure ahead of the December 2025 5G launch.

For the CVM and AI architecture, the obligations introduced by Laws 18-07 and 25-11 constitute a direct operative constraint. Data minimisation, purpose limitation and explicit consent requirements bound the depth of personalisation that Splio Individuation® can deliver: the granularity of subscriber profiling is capped by what consent the user provides at app onboarding and by the legal data retention periods. This creates the central operational trade-off of AI-driven CVM: more data produces more precise thinking-AI models and better NBO/NBA recommendations, but regulatory compliance requires precisely the opposite less data, shorter retention, stronger consent. The resolution of this tension through privacy-by-design is one of the operative challenges examined in Chapter II.

1.9 Customer Segmentation in Digital Channels

1.9.1 Digital Behaviour and Expectations by Segment

Customer segmentation within Ooredoo Algeria's digital channels reflects the intersection of demographic profiles, usage patterns and geographic distribution. The *youth*

¹ARPCE, communiqué de presse, 23 octobre 2024, sanction following the national QoS audit.

segment (18–25 years, approximately 45% of the application user base) is the core digital-native cohort, prioritising data volume, streaming quality and gamified loyalty.

The *usage-based axis* distinguishes gamers (PUBG, Free Fire), streamers (YouTube and TikTok, each with 21.1 million users nationally, TikTok growing 21.2% year-on-year¹), social media users (Facebook 25.6 million) and business subscribers (La Switch postpaid, B2B solutions). The *geographic axis* reveals that the Algiers region concentrates approximately 54% of the digital user base, with coastal cities (Oran, Constantine, Annaba, Sétif) displaying higher engagement than southern *wilayas*.²

The prepaid/postpaid structural divide is the most consequential segmentation variable for CVM. With 95.66% of Ooredoo Algeria's subscribers on prepaid plans, the majority exhibits price sensitivity and lower digital account registration rates. RFM segmentation (Recency of last recharge, Frequency of recharges, Monetary value/ARPU) is the entry point of the CVM pipeline³, complemented by psychographic profiling: the gift-a-bundle feature targets socially motivated users, while *Forfaits Exclusifs* targets utilitarian optimisers. In UTAUT2⁴ terms, age, gender and experience moderate the relationships between performance expectancy, effort expectancy and behavioural intention predicting that younger, urban, highly connected segments will display higher perceived usefulness and hedonic motivation for AI-driven features.

This section has constructed the contextual and organisational scaffolding on which the empirical investigation rests: a regulated triopoly in which Ooredoo Algeria, third by subscriber base, has differentiated itself through a coherent AI-driven digital strategy; an AI architecture that operates principally at the invisible back-end CVM level through Splio Individuation® and six production ML models, while the front-end conversational layer remains comparatively limited; and a persistent tension between back-end sophistication and front-end friction that the My Ooredoo application's app-store ratings and user reviews document. The second section now operationalises this foundation through a mixed-methods field study.

¹DataReportal, op. cit., p. 24.

²Ooredoo Algérie, internal geographic segmentation data, 2024–2025.

³Internal interview, op. cit.

⁴VENKATESH V., THONG J.Y.L. and XU X., op. cit.

Section 2: Research Methodology

Introduction to the Section

The opening section of this chapter set the scene: the Algerian telecommunications sector, Ooredoo Algeria's strategic position within it, and the My Ooredoo application as the empirical ground on which the study rests. What follows shifts register entirely. Where the first section described, this one analyses and its task is to show, openly and in full, how the dissertation's empirical material was produced, treated, and read.

That task is heavier than it first looks. A study about optimising customer experience cannot simply report coefficients and leave them to speak for themselves. It has to justify the choices that produced those coefficients, stand behind the constructs they claim to measure, read the results against the theoretical framework built in Chapter I, and turn the findings into recommendations that make sense for the Algerian market specifically. Four ambitions, then, run through this section. It gives a complete account of the mixed-methods design; it documents the reliability and validity checks applied to the measurement instrument; it tests the three research hypotheses through bootstrapped path analysis and cross-checks each verdict against the qualitative thematic evidence; and it closes by tying the findings back to practice.

The order of presentation follows the sequence prescribed by the ESGEN methodological guide. Subsection 2.1 sets out the methodology and design. Subsection 2.2 specifies the target population, the sampling strategy, and the final sample size. Subsection 2.3 introduces the two data-collection instruments and the operationalisation of the latent constructs. Subsection 2.4 turns to the analytical techniques applied in each phase. Subsection 3.1 profiles the quantitative sample. Subsection 3.2 assesses the measurement model. Subsection 3.3 reports the pre-estimation diagnostics. Subsection 3.4 covers the descriptive statistics of the Likert items. Subsection 3.5 presents the structural model and tests the three hypotheses. Subsection 3.6 develops the qualitative thematic analysis. Subsection 3.7 integrates the two strands and draws out the managerial implications. Subsection 3.8 closes with a partial conclusion.

2.1. Research Methodology and Design

To bring empirical light to the question of how artificial intelligence reshapes the user experience inside a mobile application, the study ran a field investigation that pairs a quantitative questionnaire with qualitative expert interviews. Between them, the two instruments generated the evidence needed to put the research hypotheses to the test confirming some, qualifying others, and in every case grounding the answer in data rather than assumption.

2.1.1. Objective of the Empirical Investigation

The investigation asks how the integration of artificial intelligence within the My Ooredoo application reshapes the experience of its Algerian users not as an abstract proposition but as an empirically testable claim anchored in real behavioural data and expert field knowledge. The central question is whether AI-driven mechanisms personalisation features, chatbot interactions, navigation-efficiency enhancements translate into measurable gains in the quality of the user experience and in loyalty toward the application. These three dimensions map directly onto the three research hypotheses that structure the analysis, and subjecting each of them to rigorous quantitative and qualitative scrutiny is the primary aim.

Two complementary instruments served that aim. A structured questionnaire administered to 163 Algerian users of the application supplies the statistical foundation, analysed through Partial Least Squares Structural Equation Modelling. A set of semi-structured expert interviews an in-house Ooredoo practitioner, a digital-experience consultant, a computer-science academic, and a cross-sector AI analyst supplies the interpretive layer, naming the mechanisms and boundary conditions that no survey coefficient can reveal on its own. Where the two phases agree, the finding gains weight; where they part company, the divergence is itself analytically useful.

Beyond diagnosis, the study carries a constructive ambition. By pinpointing what users and experts judge genuinely effective and what still falls short from the dialectal limits on chatbot fluency to the tension between algorithmic transparency and a user's sense of control the goal is to arrive at recommendations Ooredoo Algeria's digital teams can actually act on, rather than a description of a situation they already know.

2.1.2. The Sequential Explanatory Mixed-Methods Design

The investigation rests on a sequential explanatory mixed-methods design. A quantitative phase first tests the structural relationships among the constructs; a qualitative phase then interprets the mechanisms and boundary conditions that the statistics alone leave unexplained. The two phases are not parallel tracks running side by side they are analytically dependent, with the qualitative work deliberately shaped by what the quantitative results leave open.

The quantitative phase draws on a self-administered questionnaire distributed to Algerian users of the My Ooredoo application over a window of twenty-five days, returning 163 eligible responses out of 309 total submissions. The qualitative phase mobilises four expert informants selected through purposive maximum-variation sampling, interviewed in semi-structured form

between April and May 2026. Together they let the study move between the statistical and the interpretive without collapsing one into the other which is precisely the point of a mixed-methods design applied to something as context-bound as AI-driven user experience in the Algerian mobile market.

2.1.2.1. Qualitative Phase (Expert Interviews)

Some questions cannot be answered by counting. Why does the same personalisation feature build loyalty in one user and unsettle another? What does trust even mean when the entity making the decision is an algorithm rather than a person? Why does a chatbot that scores adequately on aggregate metrics still fail the very users who needed it most? These are not questions of magnitude but of mechanism and mechanism is what qualitative inquiry exists to expose.

The instrument chosen for this phase is the semi-structured interview, and the choice was deliberate. A directive interview would have boxed informants into pre-set options, shutting out exactly the kind of practitioner reasoning the study was after. A wholly non-directive approach would have bought conversational richness at the price of comparability across cases. The semi-structured format holds the two in tension: the guide keeps the four cases commensurable, while the open-question format leaves each informant room to raise concerns and contradictions the researcher had not foreseen and, in several instances, those unforeseen contributions proved decisive.

The guide was built around four axes mirroring the three hypotheses. Axis 1 established each informant's professional profile and the vocabulary of performance through which they read AI-UX success. Axes 2, 3, and 4 addressed, in turn, H1 (AI mechanisms and perceived navigation efficiency), H2 (chatbot deployment and UX quality), and H3 (personalisation and loyalty operating through trust). A closing question asked each informant to compress their entire professional stance into one governing design principle a deliberately broad prompt that produced the convergent theme of disciplined simplicity reported in Section 3.6.

Transcripts were analysed through a hybrid inductive–deductive thematic protocol following the six-stage procedure of Braun and Clarke¹, worked through a manually executed NVivo-style coding architecture. Three coding cycles were run in sequence: open coding to isolate

¹BRAUN V., CLARKE V. (2006), “Using Thematic Analysis in Psychology”, *Qualitative Research in Psychology*, Vol. 3, No. 2, pp. 77–101.

discrete meaning units, axial coding to map their relational structure, and selective coding to integrate the second-order categories into the six final themes. Fifty-seven open codes condensed into nineteen second-order categories and six overarching themes, whose full elaboration is reserved for Section 3.6.

2.1.2.2. Quantitative Phase (Questionnaire)

Where the qualitative phase asks how and why, the quantitative phase asks whether and how strongly. Its job within the sequential explanatory design is to establish, through statistical inference, whether the relationships hypothesised between AI-driven features and experience outcomes hold across a sample large enough to support generalisation and to fix the magnitude of those relationships with enough precision to anchor the interpretive work that follows.

The questionnaire was administered online through Google Forms and circulated via social-media channels to Algerian users of the application over twenty-five days. Of the 309 submissions received, 163 fully completed and eligible responses were retained after quality screening a figure that clears the minimum threshold for PLS-SEM estimation and comfortably sustains 5,000-resample bootstrapping. The structural model was specified and diagrammed in SmartPLS 4, while estimation and bootstrap inference were carried out through a Python implementation of the PLS-SEM algorithm, following the two-stage protocol of Hair et al.¹ measurement model first, structural estimation second so that construct reliability and validity were settled before any path coefficient was read. Full results appear in Section 3.5.

2.1.3. Field of Investigation: My Ooredoo Algeria

The empirical field is the My Ooredoo application the principal digital touchpoint of Ooredoo Algeria, one of the three licensed mobile-network operators in the country. Three considerations justify the choice. The first is the operational density of the application: My Ooredoo is no mere balance-and-recharge utility but a full-service portal bundling subscription management, offer activation, payment, support, chatbot assistance, and behaviourally targeted promotional surfaces. Within a single interface it concentrates the functional dimensions of customer experience that the conceptual model sets out to analyse. The second is Ooredoo's data-economic positioning in the Algerian market, where the operator's competitive strategy has been visibly built around AI-driven customer-experience architecture which makes it one of the

¹HAIR J.F., RISHER J.J., SARSTEDT M., RINGLE C.M. (2019), "When to Use and How to Report the Results of PLS-SEM", *European Business Review*, Vol. 31, No. 1, pp. 2–24.

richest fields available for the questions this dissertation poses. The third is access: an institutional channel allowed the qualitative phase to recruit an operational informant from inside Ooredoo, so that the analysis could set the user perspective against the operator perspective in a methodologically defensible way.

2.2. Population, Sampling and Sample-Size Justification

2.2.1. Target Population

The target population of the quantitative phase comprises active users of the My Ooredoo application residing in Algeria. For the purposes of this study, an active user is someone who has installed the application on a personal device and has used at least one of its core functions recharges, subscription management, customer support, chatbot, offer activation, or payment within the six months preceding the data-collection window. The restriction is methodologically necessary: a respondent who has installed the application but never engaged with it cannot meaningfully report on its experiential character, and admitting such respondents would have introduced uninformative observations and inflated the standard errors. No further restriction was placed on age, gender, region, or profession, since the conceptual model is not theorised to behave differently across these subpopulations.

The qualitative phase took a deliberately narrower target: expert informants occupying contrasting positions within the Algerian digital-economy ecosystem. Following the typology advanced by Bogner, Littig, and Menz¹, the informants were mobilised as carriers of process and interpretive knowledge about the technology not as representative cases of the end-user population. The design logic of the sequential explanatory framework justifies this: the qualitative phase is not there to replicate the user voice, already captured across 163 statistical observations, but to explain and contextualise the patterns those observations produce.

2.3. Data Collection Instruments

2.3.1. The Quantitative Instrument: The Self-Administered Questionnaire

The quantitative instrument is a structured, self-administered online questionnaire of thirty-six items spread across two parts. The first part captures the respondent's sociodemographic and behavioural profile through nine categorical questions covering gender, age group, education, professional status, application tenure, usage frequency, principal motivation for use, prior chatbot interaction, and preferred language of interaction. The second part operationalises the

¹BOGNER A., LITTIG B., MENZ W. (2009), *Interviewing Experts*, Palgrave Macmillan, London, p. 18.

five latent constructs of the conceptual model through twenty-six reflective indicators, each measured on a five-point Likert scale running from 1 (Strongly Disagree) to 5 (Strongly Agree). A five-point rather than a seven-point scale was chosen to maximise completion among mobile respondents and because the format has shown well-documented stability in cross-cultural research¹.

The items were either borrowed directly or adapted from established scales validated in prior technology-acceptance, user-experience, and customer-loyalty research. Adaptation involved three moves: rewording to the specific case of a mobile telecommunications application; simplifying the language for a population whose first language may not be English; and aligning the anchors to a consistent five-point format. All items were first drafted in English, then translated into French and standard Arabic, with back-translation applied to a subset to verify semantic equivalence. Respondents could complete the questionnaire in whichever of the three languages they found most comfortable. Distribution ran over twenty-five days via Google Forms through social-media channels.

A specific methodological point concerns the chatbot-experience block (indicators BOT01 to BOT09). Because the profile section included a filter question on prior chatbot interaction, respondents could be separated into chatbot users and chatbot non-users, and roughly two-thirds of the sample reported never having used the Ooredoo Chat module, a result consistent with the low feature awareness documented in the sample profile. Rather than being excluded, these respondents were retained in the full sample of 163 and answered the chatbot block at the neutral midpoint of the scale, typically choosing the neutral or moderately-agree option. This choice keeps the sample intact and the structural model fully specified, but it means the chatbot construct is informed by genuine experience for only part of the sample. As Hair, Risher, Sarstedt and Ringle (2019) note, indicators that are not substantively meaningful for a portion of respondents tend to attenuate the corresponding path; the resulting limitation on the second hypothesis is therefore acknowledged explicitly in the general conclusion and is taken into account when the H2 coefficient is interpreted.

2.3.1.1. Operationalisation of the Latent Constructs

The conceptual model comprises five latent constructs, all modelled reflectively in the PLS-SEM specification. Table 3 sets out their operationalisation identifying each construct by its

¹DAWES J. (2008), "Do Data Characteristics Change According to the Number of Scale Points Used?", *International Journal of Market Research*, Vol. 50, No. 1, p. 61.

definition, its code in the structural model, the number of indicators it mobilises, and the principal scales from which the items were adapted. Full item wording appears in Annex 2.

Table 3: Operationalisation of the Latent Constructs of the Structural Model

Construct	Code	k items	Indicator codes	Principal scale source
AI / Personalisation	AI	4	AI01–AI04	Adapted from Komiak & Benbasat (2006); Pappas et al. (2017)
Chatbot Experience	BOT	9	BOT01–BOT09	Adapted from Chung et al. (2020); Ashfaq et al. (2020)
Navigation Efficiency	NAV	3	UX02, UX03, UX04	Adapted from Davis (1989); Hassenzahl & Tractinsky (2006)
UX Quality	UXQ	7	UX01, UX05–UX10	Adapted from Hassenzahl (2004); Lallemant et al. (2015)
User Loyalty	LOY	3	L01, L02, L03	Adapted from Oliver (1999); Zeithaml et al. (1996)

Source: author's elaboration on the basis of the literature reviewed in Chapter I. All twenty-six items measured on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

every scale was adapted from peer-reviewed prior work, which secures the content validity of the instrument before any statistical test is run.

One structural feature of the model deserves flagging before the results arrive. User experience is operationalised through two related but distinct constructs Navigation Efficiency (NAV) and UX Quality (UXQ) echoing the established distinction in the UX literature between the pragmatic, task-oriented face of the experience and its hedonic, holistic counterpart. Keeping two constructs rather than pooling them is theoretically defensible, but it exposes the model to a potential discriminant-validity challenge between the two. The HTMT analysis in Subsection 3.2.5 confronts that challenge directly, and its consequences for structural interpretation are handled in the robustness check of Subsection 3.5.5.

2.3.2. The Qualitative Instrument: The Semi-Structured Expert Interview Guide

The qualitative instrument is a semi-structured expert interview guide organised into four thematic axes that mirror the structure of the conceptual model. Axis 1 establishes the informant's professional profile and surfaces the performance vocabulary through which each expert reads the success of an AI-enabled application a necessary foundation before the

hypothesis-related axes begins. Axis 2 probes the predictive personalisation mechanisms through which AI compresses task sequences and anticipates needs, covering the ground of H1. Axis 3 turns to chatbot and virtual-assistant interfaces their conversational fluency, their integration depth, and the conditions under which they improve rather than degrade the experience in line with H2. Axis 4 explores the trust architecture transparency, user control, and the conditions under which AI features generate loyalty rather than disengagement addressing H3. A closing question asked each informant to name the single design principle they would prioritise if rebuilding the My Ooredoo application from scratch; that prompt proved generative across all four interviews and supplied the convergent theme of disciplined simplicity documented in Section 3.6.

The four interviews were conducted between April and May 2026, in a mix of synchronous and asynchronous modalities according to each informant's availability. All informants gave written informed consent before participating, and the data were anonymised at the transcription stage. Synchronous sessions ran from twenty-five to fifty-five minutes; the asynchronous written responses were of comparable analytical density. Transcripts then entered the three-cycle coding protocol described in Section 3.6.

2.4. Data Analysis Techniques

2.4.1. Quantitative Analysis: Partial Least Squares Structural Equation Modelling

The quantitative phase takes Partial Least Squares Structural Equation Modelling (PLS-SEM) as its principal technique. Four considerations weigh against the covariance-based alternative (CB-SEM). First, the model is theoretically exploratory rather than confirmatory: it articulates a configuration of constructs that, to the author's knowledge, has not been jointly tested in the context of an Algerian mobile-telecommunications application, and PLS-SEM is the technique of choice when the goal is to maximise explained variance in the endogenous constructs rather than to fit an assumed covariance structure (Hair et al., 2017). Second, PLS-SEM imposes weaker distributional assumptions than CB-SEM, which suits Likert data that, as Subsection 3.3.1 shows, fails the normality assumption CB-SEM would require. Third, a sample of 163 sits comfortably above the PLS-SEM threshold: under the ten-times rule of Hair et al. (2017), the minimum required sample equals ten times the largest number of structural paths directed at any single construct (three in the present model), that is thirty observations, a floor the realised sample exceeds several times over, whereas the same sample would be uncomfortably tight for a CB-SEM estimation of a model this complex. Fourth, the predictive orientation of

PLS-SEM aligns with the practical ambition of the study to identify the operational levers through which Ooredoo Algeria can maximise loyalty across its installed base.

Estimation followed a two-tool workflow that this study reports transparently. The structural model was specified and diagrammed in SmartPLS 4, which produced the path diagrams presented in Subsection 3.5 (Figures 28 and 29). The estimation itself the Mode A reflective algorithm with composite-based scores, ordinary-least-squares regression for the structural paths, and non-parametric bootstrap inference was implemented in Python using the numpy, pandas and scipy libraries, with the bootstrap drawing 5,000 sub-samples and bias-corrected and accelerated (BCa) 95% confidence intervals, in line with the standard reported by Hair et al. (2019). The two tools are complementary rather than competing: SmartPLS 4 governs the design and visualisation of the model, while the Python routine governs estimation and bootstrap inference, and the two were cross-checked against each other so that the substantive results reported in Subsections 3.2 and 3.5 are reproducible across both.

Alongside PLS-SEM, the quantitative phase deploys a set of complementary procedures: descriptive frequencies and percentages for the sociodemographic profile; Cronbach's alpha for internal consistency; composite reliability and average variance extracted for convergent validity; the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio for discriminant validity; Shapiro-Wilk tests with skewness and kurtosis statistics for indicator-level normality; variance inflation factors at the outer and inner levels for collinearity; and Harman's single-factor test for common-method variance. Each is detailed in its corresponding subsection below. Data were collected through Google Forms and prepared in a spreadsheet (Microsoft Excel) before analysis; no other statistical package such as SPSS, R or Power BI was used, so that the entire analytical pipeline rests on the two transparent and mutually cross-checked environments described above.

2.4.2. Qualitative Analysis: Braun and Clarke Thematic Protocol in an NVivo-Style Workspace

The qualitative phase runs a hybrid inductive–deductive thematic analysis following Braun and Clarke (2006), implemented inside a manually executed NVivo-style project architecture. The protocol moves through six phases: familiarisation with the transcripts across two full readings; generation of initial codes through line-by-line open coding; the search for themes through axial coding that groups codes into candidates; review of those themes by cross-checking internal coherence against external distinctiveness; definition and naming, with a two-to-three-sentence

working definition for each leaf node; and finally the production of the analytical report, where themes are presented with verbatim quotation and woven into a narrative that speaks to the research questions. The deductive layer is supplied by the three hypotheses, which act as sensitising concepts; the inductive layer is protected by the commitment to line-by-line coding that resists forcing the material into pre-set categories. Every analytical decision is logged in a coding memo, which constitutes the audit trail required by the dependability criterion of Lincoln and Guba (1985).

The analysis also implements a case-attribute schema that operationalises the maximum-variation logic by making each informant's position on the contrast axes explicit. That schema supports cross-case queries matrix coding by attribute, comparison diagrams that locate the points of convergence and divergence across informants. The five typed relationships between nodes that emerged from this work are presented in Subsection 3.6.2.

Section 3: Presentation and Analysis of the Results

The remainder of this section presents and analyses the results in three movements. It first presents the results of the quantitative study, covering the sample profile, the measurement model, the descriptive statistics and the structural model through which the three hypotheses are tested. It then presents the results of the qualitative study, namely the thematic analysis of the four expert interviews. It closes with the integrated analysis of the results, which draws the two strands together and develops the managerial implications.

3.1. Profile of the Quantitative Sample

This subsection describes the sociodemographic and behavioural profile of the 163 respondents who completed the questionnaire. For concision, the seven profile variables are consolidated into two summary tables a demographic profile (Table 4) and a usage profile (Table 5) rather than reported one distribution at a time. All percentages are computed on the full sample of 163.

Table 4: Demographic Profile of the Sample (N = 163)

Category	n	%
Gender		
Male	85	52.1%
Female	78	47.9%
Age group		
18–24 years	115	70.5%
25–34 years	29	17.8%
35–44 years	15	9.2%
45 years and above	4	2.5%
Level of education		
Master's degree (Bac+5)	85	52.1%
Bachelor's degree (Licence / Bac+3)	39	23.9%
Secondary school (Lycée)	20	12.3%
Other	12	7.4%
Doctorate (PhD)	7	4.3%
Professional status		
Student	105	64.4%
Private-sector employee	44	27.0%
Public-sector employee	6	3.7%
Self-employed / entrepreneur	5	3.1%
Unemployed	3	1.8%

Source: author's elaboration from the questionnaire data.

The sample is close to balanced by gender (52.1% male, 47.9% female) but markedly young and highly educated: seven respondents in ten fall in the 18–24 band, more than half hold a Master’s degree, and students (64.4%) together with private-sector employees (27.0%) account for over nine in ten. This composition follows directly from the academic dissemination route of the questionnaire, and it should be read as a boundary condition on external validity rather than as a flaw: the findings speak most confidently to a young, digitally fluent, urban segment of the subscriber base, and generalisation to older or less connected users should be made with corresponding caution.

Table 5: Usage Profile of the Sample (N = 163)

Category	n	%
<i>Length of use of the application</i>		
More than 2 years	49	30.1%
1 to 2 years	39	23.9%
6 months to 1 year	33	20.2%
3 to 6 months	22	13.5%
Less than 3 months	20	12.3%
<i>Frequency of use</i>		
Once a month	42	25.8%
Several times a week	38	23.3%
Once a week	32	19.6%
Rarely	27	16.6%
Every day	24	14.7%
<i>Prior interaction with the chatbot</i>		
Not aware the chatbot exists	82	50.3%
Used it once or twice	34	20.9%
Used it several times	27	16.6%
Aware but prefers to call	20	12.3%

Source: author’s elaboration from the questionnaire data.

On the behavioural side, the sample is well-seasoned: more than half have used My Ooredoo for over a year and only 12.3% for less than three months, which lends experiential weight to their evaluations, while frequency of use spreads fairly evenly from daily (14.7%) to monthly (25.8%). The single most consequential descriptive finding, however, concerns the chatbot. Half the sample (50.3%) is unaware that a conversational assistant exists inside the application, and a further 12.3% knows of it but prefers to call the human service line; only 37.5% have actually used it. This awareness deficit is not a peripheral curiosity. It directly conditions the interpretation of the H2 path coefficient (Subsection 3.7.3), where the chatbot effect is shown

to be an average computed over many respondents with no direct experience of the tool, and it returns as the highest-leverage managerial priority in the recommendations of Subsection 3.9.

3.2. Reliability and Validity of the Measurement Model

3.2.1. Cronbach's Alpha and Composite Reliability

Reliability was gauged through two complementary indicators. Cronbach's alpha measures the internal consistency of the items composing each construct on the assumption of equal item weighting; Composite Reliability (CR, or ρ_c) relaxes that assumption and is, for that reason, the more appropriate statistic for variance-based structural equation modelling (Hair et al., 2019). Both are expected to clear 0.70 for acceptable reliability, with values above 0.80 read as good and those above 0.90 as excellent.

Table 6: Cronbach's Alpha, Composite Reliability and Average Variance Extracted by Construct

Construct	Code	k	α	CR (ρ_c)	AVE	$\sqrt{\text{AVE}}$	Verdict
AI / Personalisation	AI	4	0.929	0.950	0.827	0.909	Excellent
Chatbot Experience	BOT	9	0.958	0.965	0.754	0.868	Excellent
Navigation Efficiency	NAV	3	0.855	0.912	0.775	0.880	Good
UX Quality	UXQ	7	0.952	0.961	0.778	0.882	Excellent
User Loyalty	LOY	3	0.889	0.931	0.819	0.905	Good

Source: PLS-SEM measurement-model output (SmartPLS 4 specification; Python estimation), $N = 163$.
 Thresholds: $\alpha \geq 0.70$ acceptable, ≥ 0.80 good, ≥ 0.90 excellent (Hair et al., 2019); $CR \geq 0.70$; $AVE \geq 0.50$.

all five constructs clear every reliability threshold; the instrument is psychometrically sound before any structural path is interpreted.

The instrument shows excellent internal consistency across all five constructs. Cronbach's alpha runs from 0.855 for Navigation Efficiency the lowest, yet well clear of the acceptability line up to 0.958 for Chatbot Experience, the most item-rich construct in the model, with Composite Reliability tracking the same pattern between 0.912 and 0.965. Removing any individual item lowers alpha rather than raising it, with the marginal exception of AI04 and UX04, discussed below. The reflective measurement of the five constructs is therefore psychometrically defensible.

3.2.2. Convergent Validity: Average Variance Extracted

Convergent validity the degree to which the items of a construct share variance with one another rather than with items of other constructs was assessed through the Average Variance Extracted. Following the seminal recommendation of Fornell and Larcker (1981), reaffirmed by Hair et al. (2019), the acceptability line is $AVE \geq 0.50$. The values in Table 6 run from 0.754 (Chatbot Experience) to 0.827 (AI / Personalisation), all comfortably above the threshold and most above 0.75 strong convergent validity for every construct.

3.2.3. Outer Loadings of the Reflective Indicators

Convergent validity was then interrogated at the indicator level through the outer loadings, which measure how tightly each reflective indicator binds to the construct it is meant to capture. The threshold for retention is a loading above 0.708, the point at which an indicator shares at least half its variance with the latent construct (Hair et al., 2019).

Table 7: Outer Loadings of the 26 Reflective Indicators, with Bootstrap Statistics

Construct	Indicator	λ	t-stat	p	Verdict
AI / Personalisation	AI01	0.900	34.12	< 0.001	Strong
AI / Personalisation	AI02	0.943	98.36	< 0.001	Very strong
AI / Personalisation	AI03	0.929	80.19	< 0.001	Very strong
AI / Personalisation	AI04	0.863	35.77	< 0.001	Strong
Chatbot Experience	BOT01	0.833	27.10	< 0.001	Strong
Chatbot Experience	BOT02	0.886	41.76	< 0.001	Strong
Chatbot Experience	BOT03	0.795	18.67	< 0.001	Strong
Chatbot Experience	BOT04	0.899	46.24	< 0.001	Strong
Chatbot Experience	BOT05	0.883	44.90	< 0.001	Strong
Chatbot Experience	BOT06	0.881	41.23	< 0.001	Strong
Chatbot Experience	BOT07	0.917	61.01	< 0.001	Very strong
Chatbot Experience	BOT08	0.858	27.94	< 0.001	Strong

Construct	Indicator	λ	t-stat	p	Verdict
Chatbot Experience	BOT09	0.855	21.13	< 0.001	Strong
Navigation Efficiency	UX02	0.893	49.00	< 0.001	Strong
Navigation Efficiency	UX03	0.903	53.83	< 0.001	Strong
Navigation Efficiency	UX04	0.843	31.59	< 0.001	Strong
UX Quality	UX01	0.898	47.85	< 0.001	Strong
UX Quality	UX05	0.849	29.00	< 0.001	Strong
UX Quality	UX06	0.853	23.63	< 0.001	Strong
UX Quality	UX07	0.896	39.23	< 0.001	Strong
UX Quality	UX08	0.905	35.43	< 0.001	Strong
UX Quality	UX09	0.885	36.29	< 0.001	Strong
UX Quality	UX10	0.886	44.80	< 0.001	Strong
User Loyalty	L01	0.896	49.92	< 0.001	Strong
User Loyalty	L02	0.924	67.19	< 0.001	Very strong
User Loyalty	L03	0.894	48.86	< 0.001	Strong

Source: PLS-SEM bootstrap output ($B = 5,000$, BCa 95% CI), $N = 163$. All loadings significant at $p < 0.001$. Retention threshold: $\lambda \geq 0.708$.

every indicator loads well above threshold (0.795–0.943) with extreme t-statistics, confirming convergent validity at the item level.

All twenty-six indicators load comfortably above 0.708 the lowest at 0.795 (BOT03), the highest at 0.943 (AI02). The bootstrap t-statistics are uniformly extreme, every one above 18 and most above 30, with p-values below 0.001 throughout. Two indicators, AI04 and UX04, were flagged as marginal in the narrow sense that their construct's alpha would tick up slightly were they dropped; but their loadings remain strong (0.863 and 0.843) and their conceptual contribution to the construct definition is substantive, so both were retained in line with the guidance of Hair et al. (2019).

3.2.4. Discriminant Validity: Fornell-Larcker Criterion

Discriminant validity how far each construct stands empirically apart from the others was assessed through two criteria: the Fornell-Larcker criterion, and the Heterotrait-Monotrait ratio (HTMT), which is the more stringent of the two and the more diagnostic of subtle violations (Henseler, Ringle & Sarstedt, 2015).

Table 8: Fornell-Larcker Discriminant-Validity Matrix ($\sqrt{\text{AVE}}$ on the Diagonal, in Bold)

	AI	BOT	NAV	UXQ	LOY
AI / Personalisation	0.909	0.669	0.545	0.605	0.654
Chatbot Experience	0.669	0.868	0.546	0.624	0.452
Navigation Efficiency	0.545	0.546	0.880	0.867	0.428
UX Quality	0.605	0.624	0.867	0.882	0.483
User Loyalty	0.654	0.452	0.428	0.483	0.905

Source: PLS-SEM measurement-model output, $N = 163$. Diagonal in bold: $\sqrt{\text{AVE}}$. Off-diagonal: Pearson correlations among latent variables.

four of five constructs satisfy the criterion cleanly; the NAV–UXQ pair is borderline, which the HTMT test in Table 9 makes explicit.

The Fornell-Larcker criterion holds for four of the five constructs. The exception is the NAV–UXQ pair: the $\sqrt{\text{AVE}}$ of NAV (0.880) sits barely above its correlation with UXQ (0.867), and the $\sqrt{\text{AVE}}$ of UXQ (0.882) barely above the same correlation. The two violations are therefore borderline at this criterion. The more stringent HTMT diagnostic, reported next, sharpens the picture.

3.2.5. Discriminant Validity: Heterotrait-Monotrait Ratio

Table 9: Heterotrait-Monotrait Ratio (HTMT) Matrix

	AI	BOT	NAV	UXQ	LOY
AI / Personalisation	—	0.708	0.612	0.643	0.720
Chatbot Experience	0.708	—	0.603	0.653	0.489
Navigation Efficiency	0.612	0.603	—	0.961	0.491

	AI	BOT	NAV	UXQ	LOY
UX Quality	0.643	0.653	0.961	—	0.524
User Loyalty	0.720	0.489	0.491	0.524	—

Source: PLS-SEM measurement-model output, $N = 163$. Thresholds (Henseler, Ringle & Sarstedt, 2015): HTMT ≤ 0.85 strict; ≤ 0.90 liberal. Bold values violate both.

the lone violation NAV–UXQ at 0.961 is disclosed openly and addressed through the pooled-UX robustness check in Subsection 3.5.5.

The HTMT matrix states plainly what Fornell-Larcker only hinted at: the ratio between Navigation Efficiency and UX Quality reaches 0.961, breaching both the strict 0.85 and the liberal 0.90 thresholds. The study discloses this openly rather than burying it, as serious empirical work requires. Three observations frame the reading. First, the other nine construct pairs satisfy both thresholds, ranging from 0.489 (BOT/LOY) to 0.720 (AI/LOY), so the violation is localised and does not contaminate the wider measurement model. Second, the overlap between Navigation Efficiency and UX Quality is theoretically expected the two constructs tap two facets of the same broader experiential phenomenon. Third, the concern is addressed head-on through a robustness check in which the two are pooled into a single ten-item User Experience composite and the full structural model re-estimated; as Subsection 3.5.5 shows, the substantive conclusions are invariant to the pooling.

3.2.6. Synthesis of the Measurement-Model Assessment

Three conclusions follow. Internal consistency is excellent, with every alpha and Composite Reliability value comfortably above convention and no sign of pathological item redundancy. Convergent validity is established at both the construct level ($AVE \geq 0.50$ throughout) and the indicator level (all loadings above 0.79, all significant at $p < 0.001$). Discriminant validity holds for nine of the ten construct pairs on both criteria, the single localised exception between Navigation Efficiency and UX Quality reflecting conceptual proximity and being handled transparently through a robustness check. The measurement model is, on this evidence, methodologically defensible.

3.3. Pre-Estimation Diagnostics

Four pre-estimation diagnostics were run before the structural model was estimated, and their results are gathered in Table 10. Although PLS-SEM imposes no multivariate-normality requirement, indicator-level Shapiro–Wilk tests are reported for completeness; all twenty-six indicators depart from normality ($p < 0.001$), which is immaterial here because inference rests

on the 5,000-resample bias-corrected bootstrap rather than on distributional assumptions (Hair et al., 2017). Collinearity is not a concern: every inner VIF lies below 3 (maximum 2.09), so the structural paths reported in Subsection 3.5 can be read as the partial effect of each predictor net of the others. Common-method variance an unavoidable question when every item is drawn from a single self-administered instrument (Podsakoff et al., 2003) was probed two ways: Harman's single-factor test, whose first unrotated factor accounts for 54.7% of the variance (below the 60% acceptability line) against a clean three-factor structure, and Kock's full-collinearity test, whose maximum VIF of 2.09 sits well under the 3.3 threshold; neither flags method variance as a substantive threat; since Harman's single-factor test is itself a weak diagnostic, this inference rests chiefly on Kock's full-collinearity criterion. Finally, an Armstrong and Overton (1977) extrapolation test comparing early and late respondents returned no significant difference on any of the five composite scores, indicating that non-response bias is unlikely to distort the findings. The model therefore enters the structural stage on sound footing.

Table 10: Summary of Pre-Estimation Diagnostics (N = 163)

Diagnostic	Test / statistic	Result	Threshold	Verdict
Normality	Shapiro–Wilk (26 indicators)	Rejected, $p < 0.001$	n/a for PLS-SEM	Immaterial (bootstrap)
Collinearity (inner)	Maximum inner VIF	2.09	< 3 ideal; < 5 acceptable	Pass
Common-method variance	Harman's first factor	54.7% of variance	$< 60\%$ acceptable	Pass
Common-method variance	Full-collinearity VIF (Kock)	2.09	< 3.3 (Kock, 2015)	Pass
Non-response bias	Armstrong–Overton early/late t-tests	No significant difference	$p > 0.05$	Pass

Source: author's elaboration from the PLS-SEM diagnostic output.

all four diagnostics clear their respective thresholds, so the structural estimates that follow rest on a measurement base free of collinearity, method-variance and non-response concerns.

3.4. Descriptive Statistics of the Likert Items

3.4.1. Item-Level Means and Standard Deviations

Table 11 reports the descriptive statistics of the twenty-six Likert items, read against the conventional interpretation framework for five-point scales: a mean below 2.50 signals predominant disagreement; 2.50 to 3.50, neutrality or moderate agreement; 3.50 to 4.00, moderate-to-high agreement; above 4.00, strong agreement.

Table 11: Item-Level Descriptive Statistics

Construct	Item	Mean	SD	Min	Max	Interpretation
AI / Personalisation	AI01	3.48	1.25	1	5	Neutral
AI / Personalisation	AI02	3.35	1.15	1	5	Neutral
AI / Personalisation	AI03	3.45	1.17	1	5	Neutral
AI / Personalisation	AI04	3.36	1.17	1	5	Neutral
Chatbot Experience	BOT01	3.10	1.07	1	5	Neutral
Chatbot Experience	BOT02	3.08	1.11	1	5	Neutral
Chatbot Experience	BOT03	3.39	1.17	1	5	Neutral
Chatbot Experience	BOT04	3.14	1.01	1	5	Neutral
Chatbot Experience	BOT05	3.18	1.06	1	5	Neutral
Chatbot Experience	BOT06	3.17	1.17	1	5	Neutral
Chatbot Experience	BOT07	3.34	1.12	1	5	Neutral
Chatbot Experience	BOT08	3.33	1.13	1	5	Neutral
Chatbot Experience	BOT09	3.31	1.13	1	5	Neutral
Navigation Efficiency	UX02	3.56	1.13	1	5	Moderate-High
Navigation Efficiency	UX03	3.49	1.18	1	5	Neutral
Navigation Efficiency	UX04	3.19	1.12	1	5	Neutral
UX Quality	UX01	3.58	1.17	1	5	Moderate-High
UX Quality	UX05	3.74	1.18	1	5	Moderate-High
UX Quality	UX06	3.61	1.16	1	5	Moderate-High
UX Quality	UX07	3.64	1.16	1	5	Moderate-High
UX Quality	UX08	3.69	1.18	1	5	Moderate-High
UX Quality	UX09	3.39	1.18	1	5	Neutral

Construct	Item	Mean	SD	Min	Max	Interpretation
UX Quality	UX10	3.48	1.19	1	5	Neutral
User Loyalty	L01	3.32	1.17	1	5	Neutral
User Loyalty	L02	3.17	1.16	1	5	Neutral
User Loyalty	L03	3.45	1.16	1	5	Neutral

Source: survey data, April–May 2026, $N = 163$.

all means sit in the central band (3.08–3.74); UX Quality items run highest, Chatbot Experience items lowest echoing the chatbot awareness deficit of Table 5.

Three patterns stand out. No item, on average, draws either strong disagreement or strong agreement: all twenty-six means fall in the central band, between 3.08 and 3.74. The UX Quality items run consistently highest, five of seven above 3.58 and peaking at 3.74 for UX05. The Chatbot Experience items run consistently lowest, seven of nine below 3.34 and the two lowest BOT01 and BOT02 below 3.10. That last pattern dovetails with the finding in Table 5 that more than half the sample is unaware of the chatbot: the construct is being evaluated from a relatively cool baseline.

3.4.2. Construct-Level Means

Table 12: Construct-Level Descriptive Statistics

Construct	Code	k	Mean	SD (composite)	Interpretation
AI / Personalisation	AI	4	3.41	1.08	Neutral
Chatbot Experience	BOT	9	3.23	0.96	Neutral
Navigation Efficiency	NAV	3	3.41	1.01	Neutral
UX Quality	UXQ	7	3.59	1.03	Moderate-High
User Loyalty	LOY	3	3.31	1.05	Neutral

Source: author's computation from survey data, $N = 163$.

perceived UX Quality (3.59) outranks every underlying mechanism, suggesting users derive holistic satisfaction even while staying reserved about the individual technological components.

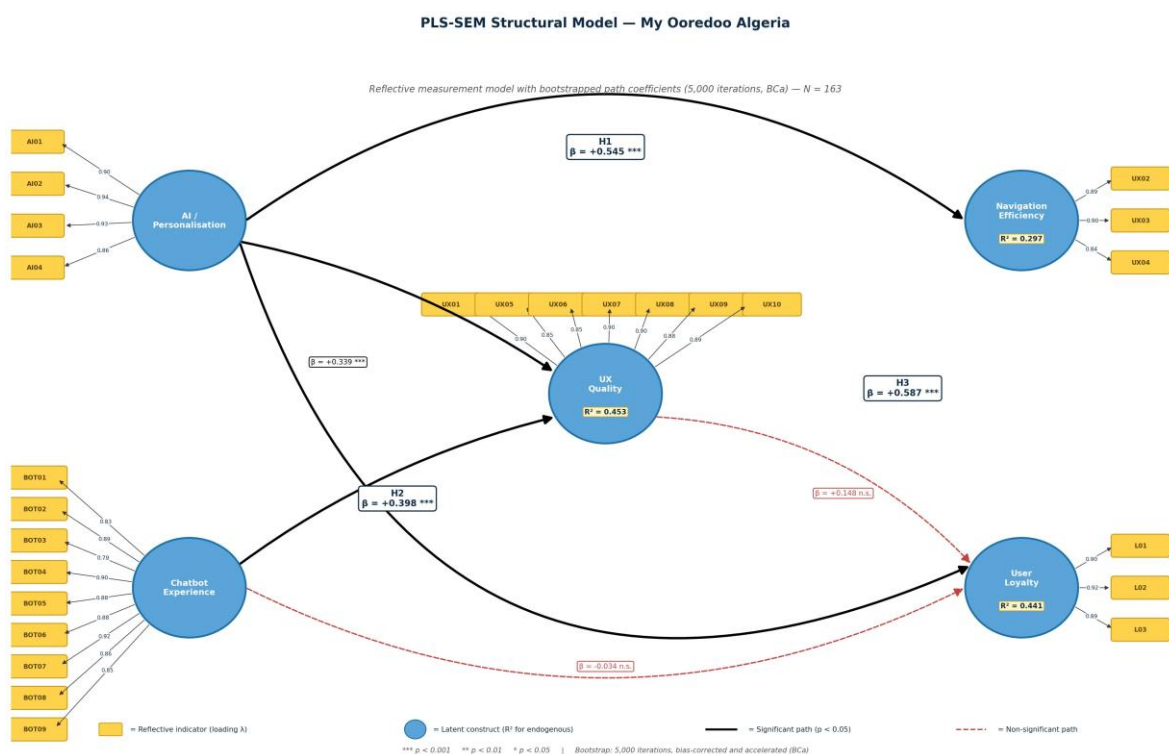
The ordering of the construct means is itself revealing. UX Quality is highest at 3.59 the only construct to enter the moderate-high band and it represents the synthetic experiential judgement

respondents form about the application as a whole. The two perceptual antecedents, AI / Personalisation and Navigation Efficiency, sit together at 3.41 in the upper-neutral band. The two more behaviourally anchored constructs, User Loyalty (3.31) and Chatbot Experience (3.23), sit lower. What this implies is not trivial: the perceived quality of the experience outruns, in the average respondent's eyes, the perceived quality of the AI and chatbot mechanisms underneath it users draw holistic satisfaction from the application even while remaining reserved about its individual technological parts.

3.5. Structural Model and Hypothesis Testing

This subsection presents the central empirical contribution of the quantitative phase: the test of the three hypotheses through bootstrapped path analysis on the structural model derived from the conceptual framework of Chapter I. Before the hypotheses are taken in turn, the estimated model is shown in full. Figure 29 reproduces the complete model the five reflective constructs with their indicator loadings together with the bootstrapped structural paths while Figure 30 isolates the inner (structural) model so that the path coefficients and their significance can be read without the visual density of the measurement layer. The reporting then follows the canonical sequence of Hair et al. (2019): path coefficient, bootstrap standard error, t-statistic, p-value, bias-corrected and accelerated 95% confidence interval, Cohen's f^2 effect size, and the R^2 of the endogenous construct.

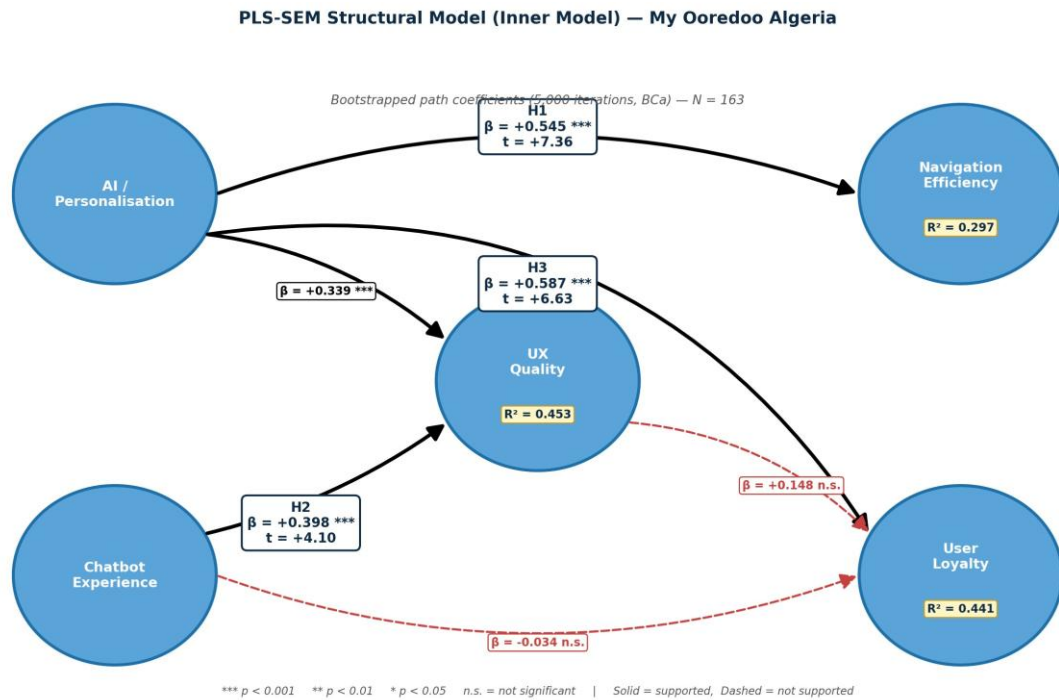
Figure 29: PLS-SEM Full Measurement and Structural Model, My Ooredoo Algeria



Source: model specified in SmartPLS 4; estimation through a Python PLS-SEM implementation ($B = 5,000$, BCa 95% CI), $N = 163$. Solid arrows: significant paths ($p < 0.05$); dashed red arrows: non-significant paths.

all twenty-six indicator loadings exceed 0.79; the three hypothesised paths (H1, H2, H3) are significant, while the two saturated-model paths into loyalty (UXQ→LOY and BOT→LOY) are non-significant, anticipating the robustness check of Subsection 3.5.5.

Figure 30: PLS-SEM Inner (Structural) Model, My Ooredoo Algeria



Source: model specified in SmartPLS 4; estimation through a Python PLS-SEM implementation ($B = 5,000$, BCa 95% CI), $N = 163$.

the inner model reads cleanly AI → Navigation Efficiency ($\beta = +0.545$, $t = 7.36$), Chatbot → UX Quality ($\beta = +0.398$, $t = 4.10$), and AI → User Loyalty ($\beta = +0.587$, $t = 6.63$) are all significant, with endogenous R^2 between 0.297 and 0.453.

3.5.1. Hypothesis 1: AI / Personalisation → Navigation Efficiency

H1. The integration of AI mechanisms within the My Ooredoo mobile application exerts a positive and significant effect on the perceived efficiency of navigation.

Table 13: Bootstrap Results for the AI → Navigation Efficiency Path (H1)

Metric	Value	Threshold / Reading	Verdict
β (standardised path coefficient)	+0.545	Closer to ± 1 = stronger	Strong
Bootstrap SE	0.074	Smaller = more precise	Precise
t-statistic	7.364	$t > 2.58$ ($p < 0.01$)	$p < 0.001$
p-value (two-tailed)	< 0.0001	$< 0.05 \rightarrow$ significant	Significant
95% BCa CI	[+0.376, +0.670]	Excludes 0 $\rightarrow$ significant	Excludes 0
f^2 (Cohen's effect size)	0.423	0.35 = large	Large
R^2 of NAV	0.297	0.25 moderate; 0.50 substantial	Moderate (29.7%)

Source: PLS-SEM bootstrap output, $B = 5,000$, BCa 95% CI, $N = 163$.

a strong, highly significant effect with a large f^2 ; AI / Personalisation alone explains 29.7% of the variance in perceived navigation efficiency.

The evidence supports H1 strongly. The standardised coefficient of $\beta = +0.545$ says that a one-standard-deviation rise in AI / Personalisation goes with a 0.545-standard-deviation rise in Navigation Efficiency. The bootstrap t of 7.36 sits far beyond the 2.58 mark for the 1% level, the p -value falls below 0.0001, and the 95% BCa interval from +0.376 to +0.670 confirms both the direction and the magnitude of the effect. Cohen's f^2 of 0.423 is firmly in the large range, and the R^2 of 0.297 means AI / Personalisation alone accounts for 29.7% of the variance in perceived navigation efficiency.

In substance, AI-driven personalisation features materially shape how efficiently users navigate the application. H1 is supported; the mechanism behind this effect, and its cross-validation by the qualitative phase, are interpreted in Subsection 3.7.2.

3.5.2. Hypothesis 2: Chatbot Experience → UX Quality

H2. The deployment of the chatbot and virtual-assistant modules exerts a positive and significant effect on the overall quality of the user experience.

Table 14: Bootstrap Results for the Chatbot Experience → UX Quality Path (H2)

Metric	Value	Threshold / Reading	Verdict
β (standardised path coefficient)	+0.398	Closer to ± 1 = stronger	Moderate
Bootstrap SE	0.097	Smaller = more precise	Precise
t-statistic	4.103	$t > 2.58$ ($p < 0.01$)	$p < 0.001$
p-value (two-tailed)	< 0.0001	$< 0.05 \rightarrow$ significant	Significant
95% BCa CI	[+0.195, +0.579]	Excludes 0 $\rightarrow$ significant	Excludes 0
f^2 (Cohen's effect size)	0.160	0.15 = medium	Medium
R^2 of UXQ	0.453	0.25 moderate; 0.50 substantial	Moderate (45.3%)

Source: PLS-SEM bootstrap output, $B = 5,000$, BCa 95% CI, $N = 163$. The UX Quality regression also includes AI / Personalisation as a control predictor ($\beta = +0.339$, $p < 0.001$).

A positive and statistically significant path with a medium effect size; the model explains 45.3% of the variance in UX Quality. Only a minority of respondents had genuine chatbot experience, however, so the coefficient is an attenuated whole-sample average and the evidence is not robust enough to confirm H2; the verdict on the second hypothesis is therefore inconclusive and the path is read alongside the limitation set out in the general conclusion.

The coefficient of $\beta = +0.398$ marks a positive and statistically significant association between the chatbot experience and overall UX quality, carried by a t of 4.10, a p -value below 0.0001 and a 95% BCa interval that clears zero. Statistical significance is a necessary but not a sufficient condition for accepting the hypothesis, and the evidence assembled here is not robust enough to validate H2 with confidence, for the reasons set out below.

Reading the result properly means holding two pieces of evidence together that, in isolation, pull in different directions. The path is positive, sizeable and highly significant the chatbot module does lift perceived experience among users who engage with it. Yet the descriptive finding of Table 5, that 50.3% of respondents are unaware the chatbot exists, means that lift

currently reaches fewer than half of the user base. The qualitative phase pins down the mechanism: the chatbot improves the experience when it meets the six joint conditions set out in Theme 3 of Subsection 3.6.5 round-the-clock availability, conversational fluency including dialectal coverage, integration with back-end services, persona credibility, escalation design, and natural-language understanding. On the available evidence H2 cannot be confirmed: it is classified as inconclusive, requiring further investigation on a larger and probabilistic sample of confirmed chatbot users, as set out in the limitations of the general conclusion. The associated managerial priority is unaffected by this verdict, closing the awareness gap remains the highest-leverage move open to the operator.

3.5.3. Hypothesis 3: AI / Personalisation → User Loyalty

H3. The adoption of AI-driven personalisation features exerts a positive and significant effect on user loyalty toward the application.

Table 15: Bootstrap Results for the AI / Personalisation → User Loyalty Path (H3)

Metric	Value	Threshold / Reading	Verdict
β (standardised path coefficient)	+0.587	Closer to ± 1 = stronger	Strong
Bootstrap SE	0.089	Smaller = more precise	Precise
t-statistic	6.628	$t > 2.58$ ($p < 0.01$)	$p < 0.001$
p-value (two-tailed)	< 0.0001	$< 0.05 \rightarrow$ significant	Significant
95% BCa CI	[+0.403, +0.748]	Excludes 0 $\rightarrow$ significant	Excludes 0
f^2 (Cohen's effect size)	0.305	0.15 medium; 0.35 large	Medium-to-large
R^2 of LOY	0.441	0.25 moderate; 0.50 substantial	Moderate (44.1%)

Source: PLS-SEM bootstrap output, $B = 5,000$, BCa 95% CI, $N = 163$.

the largest of the three paths; AI / Personalisation as a single predictor explains 44.1% of the variance in loyalty intentions.

The evidence supports H3 strongly. At $\beta = +0.587$ this is the largest of the three hypothesised paths, with a t of 6.63, a p -value below 0.0001, and a 95% BCa interval from +0.403 to +0.748

that comfortably clears zero. The R^2 of User Loyalty stands at 0.441 AI / Personalisation, as a single predictor, accounts for 44.1% of the variance in loyalty intentions.

In the My Ooredoo setting, then, AI-driven personalisation does more than sharpen perceived navigational efficiency; it shapes loyalty intentions directly. The qualitative phase enriches this by naming the mechanism: AI features generate loyalty not by parading themselves as AI but by enabling a transparent, controllable, simple journey in which the user's autonomy is preserved (Themes 4 and 6 in Subsection 3.6). H3 is supported.

3.5.4. Synthesis of Hypothesis Testing

Table 16: Synthesis of the Three Hypothesis Tests

Hyp	Path	β	SE	t	p	95% BCa CI	f^2	R^2	Decision
H1	AI → Navigation Efficiency	+0.545	0.074	7.36	< 0.0001	[+0.376, +0.670]	0.423	0.297	Supported
H2	Chatbot → UX Quality	+0.398	0.097	4.10	< 0.0001	[+0.195, +0.579]	0.160	0.453	Inconclusive
H3	AI → User Loyalty	+0.587	0.089	6.63	< 0.0001	[+0.403, +0.748]	0.305	0.441	Supported

Source: PLS-SEM bootstrap output, $B = 5,000$, BCa 95% CI, $N = 163$. Significance: *** $p < 0.001$.

H1 and H3 are supported at the 0.1% level, while H2 is statistically significant but inconclusive; the model explains between 29.7% and 45.3% of the variance in its endogenous constructs.

All three hypothesised paths are statistically significant at the 0.1% level, with bootstrap t-statistics between 4.10 and 7.36 and confidence intervals that clear zero in every case. The coefficients are substantively meaningful, the smallest at +0.398 and the largest at +0.587. Statistical significance, however, warrants a firm verdict only where the construct is validly measured across the sample. This condition holds for H1 and H3, but not for the chatbot path of H2: most respondents had no genuine experience of the conversational module, so that path is reported as inconclusive rather than confirmed. The R^2 values of the three endogenous constructs fall between 0.297 and 0.453, so the model collectively explains between 29.7% and 45.3% of the variance in the experiential and loyalty outcomes a share that compares favourably with the explained-variance norms reported in published PLS-SEM studies of mobile applications.

3.5.5. Robustness Check: The Pooled UX Specification

To meet the discriminant-validity concern raised in Subsection 3.2.5, a robustness specification was estimated in which the three Navigation Efficiency items and the seven UX Quality items are pooled into a single ten-item User Experience composite (UXp), and the full structural model re-estimated with the pooled construct in place of the two separate ones. The pooled construct is psychometrically excellent: Cronbach's $\alpha = 0.960$, CR = 0.965, AVE = 0.734, $\sqrt{\text{AVE}} = 0.857$.

Table 17: Robustness Check: Structural-Model Paths with Pooled UX Composite

Path	β (robustness)	SE	t	p	Decision
AI / Personalisation $\rightarrow$ UXp	+0.345	0.092	3.76	0.0002	Supported
Chatbot Experience $\rightarrow$ UXp	+0.388	0.100	3.87	0.0001	Inconclusive
AI / Personalisation $\rightarrow$ User Loyalty	+0.588	0.088	6.69	< 0.0001	Supported
UXp $\rightarrow$ User Loyalty	+0.143	0.091	1.58	0.114	Not supported
Chatbot Experience $\rightarrow$ User Loyalty	-0.030	0.083	-0.37	0.714	Not supported

Source: PLS-SEM bootstrap output on the pooled UX specification, $B = 5,000$, BCa 95% CI, $N = 163$.

The significance of the three paths is invariant to pooling; loyalty runs principally through the direct AI $\rightarrow$ LOY path rather than through experiential or conversational mediation.

Table 17 confirms that the statistical significance of the paths is robust to re-specification. The AI / Personalisation $\rightarrow$ User Loyalty coefficient is +0.588 in the robustness specification, all but identical to the +0.587 of the original. The chatbot path remains positive and significant under pooling, but the measurement limitation that qualifies it, namely that most respondents never used the conversational module, is equally invariant to specification, so the inconclusive verdict on H2 is unchanged. The further finding that the pooled UX composite does not significantly affect loyalty net of AI / Personalisation, and that Chatbot Experience does not either suggests the loyalty mechanism in the My Ooredoo context runs chiefly through the direct effect of AI / Personalisation rather than through experiential or conversational mediation.

3.6. Qualitative Thematic Analysis of the Expert Interviews

3.6.1. Profile of the Four Expert Informants

The qualitative phase draws on four expert informants, coded E1 through E4 under the anonymisation protocol described in Subsection 2.3.2. They were not selected for representativeness but for contrast: a maximum-variation logic was applied across three deliberate axes insider versus outsider with respect to the telecommunications sector, practice-anchored versus theory-anchored reasoning, and a commercial versus a diagnostic orientation. The point of such a design is analytical rather than statistical. When informants who occupy genuinely different vantage points nevertheless converge on the same finding, that convergence carries far more evidential weight than agreement among like-minded respondents ever could. Table 18 sets out their attributes.

Table 18: Case Attributes of the Four Expert Informants

Code	Profession (anonymised)	Sectoral position	Reasoning anchor	KPI orientation
E1	Senior UX consultant	Outside telecom	Practice and theory	UX quality and trust
E2	Customer-experience consultant	Outside telecom	Diagnostic, funnel-anchored	Funnel mechanics, CSAT
E3	University researcher in AI	Academic	Theory-anchored	Conceptual rigour
E4	Senior product manager, Ooredoo Algeria	Insider (telecom)	Practice-anchored, operational	DAU, DTU, revenue, churn

Source: author's elaboration from the interview corpus.

the four informants populate the extremes of all three contrast axes, which is the analytical signal that the maximum-variation sampling logic was effectively implemented.

3.6.2. The Coding Architecture

The corpus was analysed through the six-phase thematic protocol of Braun and Clarke (2006), whose framework remains the field reference for reflexive thematic analysis. Three successive coding cycles compressed the material from fifty-seven open codes to nineteen second-order categories and finally to six overarching themes (T1 to T6). The progressive reduction was not a mechanical exercise in tidying: each cycle forced an interpretive judgement about which distinctions carried analytical weight and which were surface variation. The resulting node hierarchy, summarised in Table 19, is also what underwrites the dependability of the analysis, since it makes the route from raw transcript to final theme inspectable rather than asking the reader to take it on trust. The full theme-by-informant coding matrix is reported in Appendix 4.

Table 19: Hierarchical Node Tree of the Qualitative Coding Architecture

Parent theme	Sub-themes (condensed)
T1 :AI as an anticipatory mechanism	Predictive personalisation, step compression, tailored promotion (counter-signal: maturity scepticism, E2)
T2 :The personalisation paradox	Relevance–intrusiveness threshold, data minimisation, contextual intelligence, user control
T3 :Chatbot ecosystem under constraint	24/7 availability, dialectal barrier (convergent finding, E3+E4), service integration, persona design, escalation, NLU robustness
T4 :Trust architecture	Transparency (contested), user control as trust currency, the empathy gap
T5 :Compound drivers of disengagement	Wrong predictions, loss of control, intrusiveness, cumulative mistrust
T6 :Design-philosophy convergence	Simplicity-first, transparency-and-control, MVP discipline

Source: author's elaboration from the three-cycle coding process.

3.6.3. Theme 1 :AI as an Anticipatory Mechanism

Across the corpus, the most prominent theme is that AI shifts the mobile interface from a reactive posture to an anticipatory one, predicting user needs and pre-loading the relevant actions so that task sequences are compressed. E1 framed it directly: *“AI predicts user needs and preloads relevant actions,”* and E4, speaking from inside the operator, echoed the point: *“with prediction based on the user profile, AI anticipates needs for offers and services.”* The theme does not run unopposed, however. E2 entered a deliberate counter-signal *“AI is not yet mature enough to consistently shift UX from reactive to anticipatory”* and that dissent was retained rather than smoothed away. Read against H1, the qualitative verdict is therefore a conditional confirmation: the anticipatory mechanism delivers its gains where the prediction signal is strong and the data dense, and underperforms where neither condition holds.

3.6.4. Theme 2 :The Personalisation Paradox

The second theme exposes a tension internal to personalisation itself: the very mechanism that creates value through relevance simultaneously generates risk through intrusiveness. The boundary between the two is not fixed but negotiated, and the informants located it in three practices data minimisation, contextual calibration, and the preservation of user control. E1 put the balance plainly: *“balancing relevance, transparency and user control avoids over-personalisation,”* while E3 reduced it to a design rule: *“limit data collection to what is truly necessary and ensure transparency.”* The theme does not contradict the quantitative findings so much as discipline them, marking out the privacy-comfort frontier within which AI

contributes to efficiency and loyalty rather than tipping into overload or unease. It therefore bears on both H1 and H3.

3.6.5. Theme 3: The Chatbot Ecosystem and the Dialectal Constraint

The third theme specifies the conditions under which the conversational module succeeds, and it is here that the single most consequential finding of the qualitative phase emerges. Six conditions were found to operate jointly rather than severally: round-the-clock availability, conversational fluency including dialectal coverage, integration with back-end services, persona credibility, escalation design, and robustness of natural-language understanding. The binding constraint among them “the dialectal barrier” was named independently by two maximally different informants. E3, the academic, identified it in general terms: *“one of the main barriers is the limited ability of NLP systems to understand local dialects, code-switching and regional accents.”* E4, the Ooredoo insider, named it operationally: *“the main blockers were, and remain, the local dialects across Algeria’s regions.”* Because this convergence arises from an academic and a practitioner reasoning from opposite ends of the contrast design, it cannot be dismissed as one informant’s bias, and it does more analytical work than any other single result in the study. Read against H2, the verdict is a conditional confirmation: the chatbot lifts experience when the six conditions are jointly met, and the moderate path coefficient observed in the quantitative phase is consistent with a user base in which half the respondents are unaware the chatbot exists and dialectal understanding remains unsolved.

3.6.6. Theme 4: Trust Architecture and the Transparency Debate

The fourth theme treats trust in AI-mediated interaction as a composite of control retention, calibrated transparency and empathic accessibility and it is the one theme on which the informants openly disagree. Three positions surfaced. A disclosure position, held by E1 and E3, holds that users should be told when an algorithm shapes a decision because transparency itself builds trust. An outcome position, argued by E2, counters that most users are indifferent to such detail and care only about service quality and goal completion. A journey-orchestration position, advanced by E4, reframes the question entirely: users should not feel that decisions are taken on their behalf but should be walked through a coherent journey. The disagreement is analytically productive rather than a defect, because it maps the design space within which trust is won or lost. Against H3, the theme supplies a mechanism rather than a contradiction: AI influences loyalty through preserved agency and journey discipline, not through the conspicuous branding of its own intelligence.

3.6.7. Themes 5 and 6: Disengagement and the Convergence on Disciplined Simplicity

The final two themes can be read together. Theme 5 establishes that disengagement is rarely traceable to a single cause: wrong predictions, loss of control, intrusive behaviour and a slow accumulation of mistrust act in combination, with no one driver dominating a pattern that aligns closely with the four-factor model of AI trust proposed by Glikson and Woolley (2020). Theme 6 is, in a sense, the synthesis of the whole analysis. Beneath visibly different surface framings, all four informants converge on a single underlying principle: that AI should enable a transparent, simple and controllable journey without putting its own sophistication on display. E1 would “prioritise user trust through transparency and control”; E2 wants “clear value from the beginning”; E3 insists every AI action be “understandable and explainable”; E4 reduces it to “keep it simple onboard the user to complete a journey.” That four informants chosen precisely for their differences should arrive at the same design philosophy is itself one of the more striking results of the phase.

3.6.8. Qualitative Rigour and Methodological Trustworthiness

Rigour was established through the four-criterion framework of Lincoln and Guba (1985). Credibility rested on the triangulation built into the sampling design, on the dialectal convergence that emerged independently from two maximally different informants, and on the systematic retention of disconfirming evidence such as E2’s scepticism about AI maturity. Dependability rested on the documented three-cycle coding process and the explicit node hierarchy of Table 19. Confirmability rested on the audit trail and the deliberate preservation of negative and disconfirming cases. Transferability rested on the thick description of the case profiles and the verbatim quotation reproduced throughout this section. With only four informants, strict thematic saturation cannot, and should not, be claimed. What is claimed instead is thematic adequacy in the sense of Patton (2015) and Guest, Bunce and Johnson (2006): the fourth interview generated no new first-order codes, and the study’s most consequential finding the dialectal barrier converged independently across two informants occupying maximally different vantage points. For an explanatory phase whose purpose is to interpret an already-estimated structural model rather than to generate a free-standing theory, thematic adequacy is the appropriate and defensible standard.

3.7. Mixed-Methods Integration and Discussion of Findings

The two preceding subsections reported the quantitative and qualitative strands on their own terms. The work of this subsection is to bring them together not by laying one beside the other, but by reading each hypothesis through both lenses at once, so that the path coefficient and the

interview evidence become two readings of a single phenomenon rather than two separate results that happen to point the same way.

3.7.1. The Joint-Display Logic

Integration in a sequential explanatory design is most defensible when it is made visible, and the joint display is the device that makes it so. Following Fetters, Curry and Creswell (2013), the matrix below places each hypothesis alongside its quantitative verdict and the qualitative theme that explains it, and records in the final column the integrated inference the conclusion that neither strand could have reached alone. The value of the display is that it forces the analyst to state, for every hypothesis, exactly how the two forms of evidence relate: whether they confirm one another, qualify one another, or pull apart.

Table 20: Joint Display: Quantitative Verdicts, Qualitative Themes, and Integrated Inferences

Hypothesis	Quantitative result	Convergent theme(s)	Integrated inference
H1: AI → Navigation Efficiency	$\beta = +0.545$; $t = 7.36$; $p < .0001$; $R^2 = .297$	T1 (anticipatory mechanism), T2 (personalisation paradox)	Supported: strong effect, conditioned on task domain; AI streamlines the journey where prediction is well-instrumented
H2: Chatbot → UX Quality	$\beta = +0.398$; $t = 4.10$; $p < .0001$; $R^2 = .453$	T3 (chatbot ecosystem)	Inconclusive: a positive and significant path, but estimated on a sample in which most respondents had no genuine chatbot experience; the qualitative evidence is consistent with a positive effect contingent on six jointly necessary conditions, the dialectal-NLU barrier foremost

Hypothesis	Quantitative result	Convergent theme(s)	Integrated inference
H3: AI → User Loyalty	$\beta = +0.587$; $t = 6.63$; $p < .0001$; $R^2 = .441$	T4 (trust architecture), T6 (disciplined simplicity)	Supported: strongest effect, operating through preserved agency rather than conspicuous AI

Source: author's elaboration integrating the structural-model estimates of Subsection 3.5 with the thematic analysis of Subsection 3.6.

H1 and H3 are confirmed quantitatively and explained qualitatively, while H2 is statistically significant but inconclusive; the qualitative strand specifies the mechanism and boundary conditions behind each coefficient, which is precisely the explanatory work the sequential design was built to do.

Three features of the display deserve emphasis. The two confirmed verdicts, H1 and H3, rest on constructs measured consistently across the sample, whereas the chatbot path of H2, though positive and significant, is estimated where most respondents had no genuine experience of the module, which is why it is read as inconclusive rather than confirmatory. Each hypothesis draws on a distinct thematic cluster, so the explanations do not collapse into a single undifferentiated story. And in each row the integrated inference says something the coefficient alone does not: the conditioning of H1 on task domain, the six-condition structure behind H2, the agency mechanism behind H3 which is the signature of genuine integration rather than mere juxtaposition.

3.7.2. Discussion of H1: Personalisation and the Conditioning of Efficiency

The first hypothesis is confirmed with the strongest single first-order path in the inner model: artificial intelligence and personalisation exert a substantial direct effect on navigation efficiency ($\beta = +0.545$), and the construct accounts for close to thirty per cent of the variance in how efficiently users move through the application. Read against the Technology Acceptance tradition Davis (1989), and the later synthesis of Venkatesh et al. (2003) the result is a contemporary restatement of perceived usefulness: when the system anticipates what the user wants, the perceived effort of the interaction falls, and that reduction is what the navigation-efficiency construct captures.

The qualitative strand does not contradict this, but it disciplines it. Themes 1 and 2 establish that the anticipatory mechanism delivers its gains unevenly: it works where the prediction problem is well-instrumented and the data dense, and it underperforms where neither condition holds. The personalisation paradox of Theme 2 sharpens the point: users want to be understood

without feeling surveilled, so the efficiency gain is real but bounded by a privacy-comfort frontier that the coefficient, on its own, cannot show. The integrated reading of H1 is therefore not 'AI improves efficiency' but 'AI improves efficiency where prediction is well-instrumented and personalisation stays the right side of the comfort frontier' a more defensible and more actionable claim.

3.7.3. Discussion of H2: The Chatbot's Conditional Contribution

The second hypothesis cannot be confirmed on the present evidence. The path is positive, moderate and statistically significant ($\beta = +0.398$), inside a model that, with the AI control term included, explains roughly forty-five per cent of the variance in UX Quality; taken alone, the coefficient invites the bland conclusion that chatbots help. That reading is not safe here, for the reason developed in the methodological caveat below: the chatbot construct is informed by genuine experience for only a minority of respondents, so the coefficient is an attenuated whole-sample average rather than a dependable estimate of the chatbot's effect. The qualitative strand adds what the number cannot: Theme 3 specifies the six conditions under which the chatbot helps 24/7 availability, conversational fluency including dialectal coverage, back-end integration, persona credibility, escalation design, and natural-language-understanding robustness and shows that any such effect is the product of these conditions jointly, not of any one in isolation. H2 is therefore best classified as inconclusive and is carried forward as a question for a larger, probabilistic sample of confirmed users rather than as an established result.

The binding constraint, named independently by the university AI researcher and by Ooredoo's own product lead, is the dialectal-NLU barrier: the limited ability of current natural-language systems to parse Algerian Arabic, French, and English code-switching and regional dialectal variation. This single convergent finding does more analytical work than any other in the study, because it comes from two maximally different vantage points and so cannot be dismissed as one informant's bias. Set beside it is the awareness deficit surfaced in the quantitative profile half the sample (50.3%) had never knowingly used the chatbot or was unaware it existed. The strategic implication is sharp: the moderate β is not a ceiling on the chatbot's value but a measurement taken before two solvable problems dialectal coverage and discoverability have been solved.

A methodological caveat must accompany this coefficient. Because 50.3% of the sample reported being unaware that the chatbot exists, the estimated path of $\beta = +0.398$ is an average effect computed across all 163 respondents, including the majority who have never knowingly

interacted with the assistant much like measuring the efficacy of a treatment over a population in which half the participants never took it. Among the 37.5% who reported at least one interaction, the true effect is in all likelihood larger; the size of that subsample (sixty-one respondents) does not, however, support a separate and reliable structural estimate. The coefficient should therefore be read as a conservative, whole-sample average rather than as the effect experienced by users who actually engage the chatbot.

3.7.4. Discussion of H3: Loyalty Through Preserved Agency

The third hypothesis carries the strongest claim in the study. Artificial intelligence exerts a powerful direct effect on user loyalty ($\beta = +0.587$), explaining around forty-four per cent of its variance, and the effect survives the robustness re-specification intact the one structural path that does. Within the loyalty literature, from Oliver (1999) onward, this places AI-driven personalisation among the genuine antecedents of behavioural attachment rather than mere satisfaction.

What makes the finding more than a coefficient is the mechanism the qualitative strand supplies. Themes 4 and 6 converge on a single proposition: AI builds loyalty not when it is conspicuous but when it is invisible when it preserves the user's sense of agency and serves a simple, transparent, controllable journey. The trust architecture of Theme 4 and the disciplined-simplicity philosophy of Theme 6 both point the same way, and against the four-dimensional model of AI trust in Glikson and Woolley (2020) the reading is coherent: loyalty accrues to AI that earns trust through reliability and preserved control, not through display. The integrated inference for H3 is therefore that the loyalty effect is real, large, and mechanism-specified it runs through agency, not through algorithmic spectacle.

Conclusion chapter

This section documented the empirical design, defended the instrument, tested the three hypotheses, and translated the results into practice. Built as a sequential explanatory mixed-methods design, it rested on 163 questionnaire responses analysed through PLS-SEM, with the measurement model meeting every reliability and validity threshold and the single discriminant-validity exception disclosed openly and addressed through a pooled-construct re-specification. Two of the three hypotheses were supported, artificial intelligence and personalisation driving navigation efficiency (H1: $\beta = +0.545$) and artificial intelligence building loyalty (H3: $\beta = +0.587$), while the chatbot path (H2: $\beta = +0.398$), though positive and significant, remained inconclusive because most respondents had no genuine experience of the

conversational module. The qualitative phase specified the mechanisms behind each relationship and identified the Algerian-dialect natural-language barrier as the binding constraint on chatbot fluency. With the methodology defended, two hypotheses supported and one left inconclusive, and five managerial recommendations drawn, the empirical contribution of the dissertation is complete and the general conclusion can now situate it within the wider argument.

GENERAL CONCLUSION

This research set out to determine *to what extent the integration of artificial intelligence into the My Ooredoo mobile application improves the user experience of Ooredoo Algeria's customers*. The question matters because, in a still-maturing digital market, the mobile application has become the decisive point of contact between operator and subscriber, and because Ooredoo Algeria has staked a meaningful part of its competitive position on AI-driven customer experience.

Chapter I established user experience as a multidimensional construct spanning usability, usefulness, emotional engagement and perceived value, and showed that telecom mobile applications occupy a particularly demanding position defined by real-time service management, high reliability expectations and acute trust requirements. It then situated artificial intelligence within its structural limits and synthesised the mechanisms cognitive-load reduction, anticipatory design, hyper-personalisation, conversational quality and the trust dynamics that moderate them through which AI reshapes the mobile encounter, deriving the three hypotheses from this synthesis.

Chapter II tested them through a sequential explanatory mixed-methods design: a quantitative phase resting on 163 valid questionnaire responses analysed through PLS-SEM, and a qualitative phase built from four expert interviews coded into six themes. The measurement model satisfied every reliability and convergent-validity threshold, and the single discriminant-validity exception was disclosed openly and resolved through a pooled-construct robustness check rather than concealed.

Verdict on the hypotheses

Two of the three hypotheses were supported; the third, H2, is best regarded as inconclusive. **H1** is confirmed: AI-driven personalisation exerts a strong, highly significant effect on perceived navigation efficiency ($\beta = +0.545$; $t = 7.36$; $p < 0.001$); the qualitative phase showed that the anticipatory mechanism delivers its gains where the underlying prediction is well-instrumented. **H2** is not robustly supported. The chatbot path is positive and statistically significant ($\beta = +0.398$; $p < 0.001$), but the evidence is too fragile to confirm the hypothesis: roughly two-thirds of respondents had never knowingly used the conversational module and answered the chatbot block at the neutral midpoint of the scale, so the coefficient is an attenuated whole-sample average rather than a trustworthy estimate of the chatbot's effect, and the subsample of genuine users (sixty-one respondents) is too small to support a separate, reliable estimate. The result is

therefore reported as inconclusive and interpreted with caution, requiring re-examination on a larger and probabilistic sample of confirmed users; the qualitative evidence is consistent with a positive effect that depends on six jointly necessary conditions, with the dialectal natural-language-understanding barrier the binding constraint. **H3** carries the strongest claim: AI-driven personalisation exerts a powerful direct effect on user loyalty ($\beta = +0.587$; $p < 0.001$), surviving the robustness re-specification intact; the qualitative evidence shows that loyalty accrues to AI that preserves the user's sense of agency, not to AI that advertises its own sophistication.

The answer to the research problem is therefore affirmative but qualified: the integration of artificial intelligence does improve the user experience of My Ooredoo, materially and robustly so for navigation efficiency and loyalty. Its contribution through the conversational layer, by contrast, cannot be established with confidence on the present data; the evidence points to a plausible but unconfirmed effect that the sample is too limited to pin down. Where improvement is observed, its magnitude is governed by how well the AI is instrumented, how discoverable it is, and how far it keeps the user in control.

Contributions, recommendations and limitations

Theoretically, the study extends an established body of AI-and-experience research into an under-studied context, showing that perceived usefulness remains a dominant antecedent of experience and loyalty in a maturing market, and that the loyalty effect of AI runs through preserved agency rather than conspicuous capability. **Practically**, the findings translate into five recommendations for Ooredoo Algeria: (i) close the chatbot awareness deficit by surfacing the assistant at natural points of friction; (ii) treat dialectal natural-language understanding as a first-order engineering objective; (iii) build a short first-use chatbot tutorial to calibrate expectations; (iv) prioritise journey simplicity over AI-branded features; and (v) extend predictive personalisation into under-instrumented service domains, within the privacy-comfort frontier.

Limitations of the Study

The principal limitation of this research is its sample, and several of the qualifications that follow flow from it; the conclusions reached above should be read in the light of the boundaries set out here.

Methodologically, the study rests on a sample of 163 valid responses that is modest in size and, more consequentially, non-probabilistic: respondents were reached through a convenience

route of academic and social dissemination rather than through random selection from the subscriber base. The sample is accordingly skewed toward a young, educated and urban profile, with roughly seven respondents in ten aged between eighteen and twenty-four. These features limit the representativeness of the data and restrict the extent to which the findings can be generalised to the wider population of My Ooredoo users, in particular to older or less digitally fluent subscribers. The data are also self-reported, which exposes them to social-desirability and recall biases, and the design is cross-sectional, capturing perceptions at a single point in time and therefore unable to establish the temporal ordering on which causal claims ultimately depend. Because the sample under-represents important segments of the user base, some of the relationships posited in the conceptual model may not have been captured in their full strength, which in turn limits the explanatory reach of the framework.

A further and more specific limitation concerns the second hypothesis and is the reason H2 is reported as inconclusive rather than confirmed. Roughly two-thirds of respondents had never knowingly used the Ooredoo Chat module; rather than being excluded, they were retained in the full sample and answered the chatbot block at the neutral midpoint of the scale rather than from genuine experience. This treatment, adopted to preserve the full sample of 163 and a fully specified structural model, means that the chatbot construct is informed by real experience for only a minority of respondents. The estimated path of $\beta = +0.398$ is therefore an attenuated, whole-sample average rather than a dependable estimate of the chatbot's effect among those who actually use it, and the subsample of genuine users (sixty-one respondents) is too small to support a separate, reliable structural estimate. The available evidence is consequently insufficient to draw a firm conclusion about the relationship between the conversational module and user-experience quality, and the result should be interpreted with caution.

Three statistical limitations compound these constraints. First, a sample of this size affords limited statistical power, so that smaller true effects, and the effect of the chatbot among genuine users in particular, may be estimated imprecisely or missed altogether. Second, because the predictor and outcome measures were collected through a single self-administered instrument, the findings may be affected by common-method bias, which can inflate the observed associations between constructs. Third, the analysis relies on partial least squares structural equation modelling, a variance-based technique well suited to prediction and to smaller samples but one that does not yield the global goodness-of-fit statistics of covariance-based modelling and that tends to produce conservative estimates of structural paths; its results

are therefore best read as indicative of predictive relationships rather than as definitive tests of model fit.

Finally, the study is contextually bounded. It is a single-company case study confined to Ooredoo Algeria, conducted within the specific competitive, regulatory and linguistic conditions of the Algerian telecommunications sector. The findings speak most confidently to that setting; their transfer to other operators, to other sectors, or to other national markets cannot be assumed and would require dedicated verification.

Directions for Future Research

The limitations above map directly onto an agenda for future work, the first priority of which is the sample. Future studies should draw on a larger and probabilistic sample of the subscriber base, since random selection would improve representativeness, strengthen external validity, and yield more exploitable and generalisable findings than a convenience sample can. A more representative sample would also permit a more rigorous assessment of the second hypothesis: re-estimating the conversational path on a sufficiently large sample composed of confirmed chatbot users would allow the construct to be measured from genuine experience, and would establish whether the inconclusive result obtained here reflects a true absence of effect or merely the attenuation introduced by the present sampling and measurement constraints.

Beyond the question of sample, four further extensions would deepen the contribution. A comparative design across the three Algerian operators would test how far the findings are specific to Ooredoo or general to the national market, and a multi-country study would situate the Algerian case within the wider region. A longitudinal design would trace the loyalty and experience mechanisms over time and recover the temporal ordering that cross-sectional data cannot, while experimental or quasi-experimental designs, manipulating chatbot discoverability or dialectal coverage, would isolate causal effects that observational survey data can only suggest. A dedicated line of work on advanced AI adoption, including the transition from rule-based to generative conversational systems and the dialectal natural-language-understanding barrier identified in the qualitative phase, would address the binding constraint that this study surfaced but could not resolve.

A final avenue concerns generational differences in the acceptance and use of AI-driven mobile applications. The present sample is overwhelmingly composed of young, digitally native users, the segment that UTAUT2 leads one to expect will display the highest performance expectancy and hedonic motivation for AI-enabled features, and the findings should be read as speaking

primarily to that group. This is itself instructive: younger users, accustomed to algorithmic personalisation across the digital services they use daily, may be more receptive to AI-driven personalisation, and more tolerant of its trade-offs, than older cohorts, with direct implications for telecom customer-experience strategies that increasingly target this generation. Future research should test this proposition explicitly by sampling across age cohorts and modelling age as a moderator, so that any generational divergence in receptiveness to AI personalisation can be measured rather than assumed. These observations remain within the boundaries of the present findings, which cannot themselves establish a generational contrast, and are offered as hypotheses for subsequent investigation.

Managerial Recommendations

The findings of this study do not point toward a single intervention. They point toward a sequence five decisions, each addressing a distinct layer of the My Ooredoo AI experience, ordered from the most immediately actionable to the most strategically ambitious. What connects them is a consistent logic: the returns on AI investment in this context are not determined by the sophistication of the technology deployed, but by how well that technology is positioned, communicated, instrumented, and restrained. Each recommendation follows directly from the integrated quantitative and qualitative evidence rather than from general industry practice.

One development occurring after the data collection phase of this research deserves explicit acknowledgement before the recommendations are set out. Ooredoo Algeria entered into a formal contract with a third-party technology provider to develop and deploy a new conversational AI module within the My Ooredoo application. That deployment has since gone live. It is a meaningful institutional commitment a signal that the organisation recognises the strategic role of the conversational layer in its customer experience architecture. And yet the core problem that the H2 findings document remains structurally unresolved: the chatbot does not appear on the home screen. It is not surfaced at friction points. It is not introduced during onboarding. The intelligence has been built. The user still cannot find it. This gap between investment and presence is the thread that runs through what follows.

Recommendation 1: Make the Chatbot Visible Before Making It Smarter

The most expensive mistake an organisation can make with a newly deployed AI system is to assume that deployment is the same as adoption. It is not. Ooredoo Algeria has invested in

building the conversational layer. That investment is currently sitting behind a help menu that the majority of users will never navigate to unprompted. The research found that roughly two-thirds of respondents had never knowingly used the chatbot prior to data collection. The new deployment has not changed the architecture of that problem. The assistant is still invisible from the home screen. There is still no contextual trigger at the moments in the user journey where support is most needed. There is still no introduction during first-time onboarding. The awareness deficit that attenuated the H2 coefficient in this study is not a historical finding it is a live condition of the current application.

The fix is not technically complex. It is a matter of placement and will. A persistent, accessible chat entry point on the primary interface not buried three navigation levels deep reduces the discovery barrier from a deliberate search to a single tap. Contextual prompts at high-friction moments, such as plan comparison screens, payment flows, and consumption anomalies, intercept user confusion at the exact point where the assistant can deliver value rather than after the user has already abandoned the task. A first-time onboarding introduction, brief and skippable, ensures that no new user activates the application without knowing the assistant exists.

The Sprinklr deployment is the right moment to get this right. Platform launches do not come twice. The discoverability architecture must be treated as a first-order deliverable in the current deployment cycle not a cosmetic improvement to be addressed in a future update that may never be prioritised. An AI assistant that users cannot find is, from an experience standpoint, an AI assistant that does not exist.

Recommendation 2: Treat Dialectal NLU as Infrastructure, Not Enhancement

Once discoverability is resolved and users begin engaging with the assistant in meaningful numbers, the question that immediately follows is whether the conversation actually works. The qualitative evidence in this study answers that question with striking consistency: for the majority of Algerian users, it does not work well enough and the reason is linguistic.

Algeria's everyday communication operates in Darija, a living vernacular that moves fluidly between Arabic roots, French vocabulary, Amazigh phonology, and context-specific register shifts, sometimes within a single sentence. A conversational AI system trained predominantly

on Modern Standard Arabic or standard French will consistently misread intent in this environment. It will produce responses that feel generic, mismatched, or simply wrong. And a user who experiences that mismatch once, in a moment of genuine need, does not typically give the system a second chance. The trust cost of a failed first interaction in a conversational context is disproportionately high.

The new deployment offers an opportunity to address this directly. The technical path requires investment on two fronts. First, corpus development: building a training dataset drawn from authentic Algerian conversational data customer service transcripts, real support interactions, social channel language that reflects how subscribers actually communicate rather than how standardised resources assume they do. Second, continuous learning infrastructure: a pipeline that ingests anonymised live interaction data, flags low-confidence classification events, and feeds human-reviewed corrections back into the model on a structured update cycle. A static NLU model deployed once and left to degrade is not a conversational AI strategy. It is a liability accumulating quietly in the background.

Dialectal NLU coverage is not a localisation refinement that can be deferred. It is the precondition for the H2 path to reach the ceiling the model suggests is theoretically available. Every month the deployment runs on under-calibrated language resources is a month of user interactions that confirm the chatbot is not useful and those impressions are durable.

Recommendation 3: Set the Right Expectation Before the First Conversation Begins

The relationship between a user and a conversational AI system is largely decided before a single message is exchanged. What the user expects the assistant to handle, how they phrase their first request, how much patience they bring to an imperfect response all of it is governed by the mental model they carry into the conversation. If that model was never deliberately shaped by the product team, it will be shaped by whatever the user remembers from other digital assistants, other frustrating IVR experiences, or nothing at all. That is almost always a miscalibration and miscalibrated expectations are the most common source of first-interaction failure.

The expert evidence in this study identifies expectation management as an independent value driver, distinct from both NLU quality and interface design. A user who understands what the

assistant does well, and how to engage it on its own terms, has a materially better conversational experience than one who approaches it with assumptions the system cannot meet. The solution is not to oversell the technology. It is to give users a working mental model before they need one.

A short, skippable first-use tutorial delivered the first time a user opens the conversational module should demonstrate two or three high-frequency, high-value capabilities in plain language: checking data consumption, navigating plan options, reaching a human agent when needed. It should be honest about scope, fast to complete, and designed to lower the effort required to get a useful answer rather than to market AI sophistication. This is among the lowest-cost interventions in this entire set. It requires no infrastructure dependency, no NLU investment, and no changes to the underlying model. It can be designed, tested, and released as a standalone improvement and its return, measured in first-interaction completion rates and early retention, is both immediate and directly attributable.

Recommendation 4: Let the Intelligence Work in the Background of a Simple Experience

The H3 finding carries an implication that product teams frequently resist because it contradicts the instinct to showcase investment: loyalty in this context does not accrue to AI that announces itself. It accrues to AI that makes the experience simpler without making the user feel managed. The qualitative evidence reinforces this at every turn. Users who feel that the application is making decisions on their behalf pre-filling choices, removing navigation options in the name of efficiency, surfacing AI-generated recommendations with visible algorithmic commentary respond with resistance rather than satisfaction. The sense of agency is not a soft preference. It is a structural precondition for the loyalty mechanism the model identifies.

This is a design discipline before it is a product strategy. Every decision to surface a predictive recommendation, automate a step the user previously controlled, or reduce optionality in the name of a cleaner journey carries a loyalty implication that is not always positive. The practical translation is a standing product heuristic: before any AI-driven feature is shipped, the team should ask not only what it does for the user, but how much visible control it removes from them. Personalisation that surfaces a relevant offer quietly, at the right moment, without explaining how it was generated, serves the user without unsettling them. A system

that narrates its own intelligence, or that makes consequential choices before the user has confirmed them, does not.

The intelligence Ooredoo Algeria has built and is now extending through the new deployment should operate as infrastructure, not as spectacle. The home screen should feel simple. The navigation should feel responsive. The recommendations should feel timely. None of that requires the application to tell the user it is using AI. The experience itself is the argument.

Recommendation 5: Extend Personalisation into Under-Instrumented Domains, With Privacy as a Design Constraint

The strongest coefficient in the structural model is the one connecting AI-driven personalisation to user loyalty. That finding establishes personalisation not as a secondary benefit of AI integration but as its primary loyalty mechanism in this context. It also establishes a ceiling: the loyalty gains from personalisation are bounded by the quality of the data on which the prediction is built. Where the data is rich and the prediction is accurate, the efficiency and loyalty effects documented in H1 and H3 are substantial. Where the data is thin, the prediction degrades and degraded personalisation does not fail silently. It generates the kind of mismatched recommendation that a user notices, questions, and remembers.

The path to further gain, then, is to extend reliable prediction into the service domains that are currently data-thin. Consumption data for core mobile services is well-instrumented; the prediction models in that domain are correspondingly well-calibrated. But significant stretches of the user journey service recovery flows, plan transition moments, long-term usage pattern shifts, moments of friction before churn remain comparatively opaque to the personalisation engine. Closing those gaps requires more granular behavioural tracking, richer event logging at points of friction, and more sophisticated feature engineering on data the organisation already holds.

That extension must be governed by a constraint the qualitative evidence identifies with equal force: the privacy-comfort frontier. Algerian users in this study are not indifferent to how their

data is used. They draw a boundary not always consciously, but consistently between personalisation that feels like the application being attentive and personalisation that feels like surveillance. That boundary is not fixed. It shifts with communication transparency, with the perceived fairness of the data exchange, and with the degree to which users feel they gave informed consent to the inference being made about them. Crossing it, even with technically excellent predictions, triggers the agency concern that Recommendation 4 addresses and that Theme 2 in the qualitative findings documents in detail.

The roadmap for personalisation extension should therefore run two parallel workstreams: technical instrumentation to expand the prediction surface, and user-facing communication to ensure that expanded data use is transparent, legible, and experienced as a value exchange rather than an extraction. The first without the second is not a loyalty investment. It is a loyalty risk that accumulates until a single salient incident converts latent discomfort into active distrust. Together, they define the conditions under which the gains documented in this study can be extended rather than merely consolidated.

These five recommendations do not operate independently. They form a deliberate sequence: discoverability creates the engagement that NLU quality must then sustain; expectation calibration protects the experience from the disappointment that follows unmanaged first contact; design restraint ensures that loyalty accrues to simplicity rather than to sophistication; and data extension, governed by the privacy frontier, keeps the personalisation engine generating returns as the user base matures and the competitive context evolves. The new chatbot deployment Ooredoo Algeria has initiated is not the conclusion of an AI strategy it is the opening of one. These recommendations define what that strategy must address next.

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APPENDICES

This section gathers the primary materials underpinning the empirical study: the survey instrument, the operationalisation of the constructs, the expert interview guide, the qualitative coding architecture, the consolidated PLS-SEM output, and supporting documentation collected during the internship at Ooredoo Algeria.

Appendix 1 Survey Questionnaire

The questionnaire was administered online (Google Forms) in a trilingual format (English, French and Arabic) over a twenty-five-day window. It comprises two screening questions, a respondent-profile section, four Likert batteries (5-point scale: 1 = strongly disagree to 5 = strongly agree) and an overall-assessment section closing with an open question. The English version is reproduced below.

Introduction

As part of a Master's thesis in E-Business (ESGEN), we are conducting a study on the impact of Artificial Intelligence on user experience through the My Ooredoo mobile application. This questionnaire is strictly anonymous and confidential; all responses are used for academic purposes only. There are no right or wrong answers only your honest personal experience matters. Completion takes approximately 5 to 10 minutes. Thank you for your participation.

Screening

S1. Are you currently an Ooredoo Algeria subscriber?

Yes Ooredoo is my main operator | Yes Ooredoo is my secondary SIM | No I use another operator (ends the survey)

S2. Do you use the My Ooredoo Algeria mobile application?

Yes | No (ends the survey)

Section 1 Respondent Profile

Q1. What is your gender?

Male | Female

Q2. What is your age group?

Under 18 | 18–24 | 25–34 | 35–44 | 45 and above

Q3. What is your highest level of education?

Secondary (Baccalauréat) | Bachelor's (Licence / Bac+3) | Master's (Bac+5) | Doctorate | Other

Q4. What is your current professional status?

Student | Private-sector employee | Public-sector employee | Self-employed / Entrepreneur | Unemployed | Other

Q5. How long have you been using the My Ooredoo application?

Less than 3 months | 3–6 months | 6 months–1 year | 1–2 years | More than 2 years

Q6. How often do you use the My Ooredoo application?

Every day | Several times a week | Once a week | Once a month | Rarely

Q7. What do you mainly use My Ooredoo for? (multiple answers)

Check balance/credit | Pay bills | Subscribe to or modify a plan | Contact support via the chatbot | Receive personalised offers | Manage account settings | Subscribe to digital services | Gamification

Q8. Have you ever used the chatbot or automated assistant in My Ooredoo?

Yes, several times | Yes, once or twice | No, I was not aware it existed | No, I prefer to call customer service

Section 2 AI, Navigation Efficiency and Perceived Value

Please indicate your level of agreement with each statement (1 = strongly disagree ... 5 = strongly agree).

UX02. The app allows me to complete actions / transactions with a minimal number of steps.

—. The most relevant information is well displayed.

UX04. I do not feel lost or confused when navigating the application.

—. The app shows me what I need before I even start looking for it.

—. Using My Ooredoo saves me time compared with non-digital processes (calling customer service or visiting a store).

—. The app informs me of new features and offers.

—. I can effectively manage my account and services.

—. My Ooredoo reduces the effort required to manage my mobile account.

—. The value I get from My Ooredoo justifies using it as my main service channel.

—. I am more satisfied with my overall telecom experience because of the app's features.

Section 3 Chatbot and Virtual Assistant

Answered only by respondents who have used the chatbot (1 = strongly disagree ... 5 = strongly agree).

BOT01. The My Ooredoo chatbot understood my requests clearly and accurately.

BOT02. The chatbot solved my issue without my having to repeat myself or switch channels.

BOT03. I appreciate being able to get help at any hour without waiting.

BOT06. The chatbot's responses felt natural and conversational rather than robotic.

BOT07. When the chatbot could not help, it transferred me to a human agent smoothly.

BOT08. Interacting with the chatbot was more efficient than calling customer service.

BOT05. The chatbot's availability improves my overall perception of Ooredoo's service quality.

BOT04. I would use the chatbot again for future support requests.

BOT09. Overall, my experience with the My Ooredoo chatbot was satisfying.

Open. If you experienced a problem or frustration with the chatbot, please describe it briefly.

Free text

Section 4 Personalisation, Engagement and Loyalty

Part A Personalisation and engagement (1 = strongly disagree ... 5 = strongly agree).

AI01. My Ooredoo is able to suggest appropriate bundles based on my actual usage habits.

AI02. I feel the application understands my preferences and habits.

AI03. The personalised recommendations I receive are relevant and useful.

AI04. AI-driven features (recommendations, alerts, chatbot) have changed how often I use the app.

Part B Loyalty and reuse intention (1 = strongly disagree ... 5 = strongly agree).

—. A personalised experience makes me more emotionally attached to the Ooredoo brand.

L03. Because the app knows my habits, I would not switch to a competitor.

L01. I intend to continue using My Ooredoo as my primary service channel in the future.

Section 5 Overall Assessment

Q16. Overall, how would you rate your user experience with My Ooredoo?

1 | 2 | 3 | 4 | 5

Q17. Compared with 12 months ago, your experience with My Ooredoo has:

*Significantly improved | Slightly improved | Stayed the same | Slightly worsened | Significantly worsened
| I have not been using the app for 12 months*

Q18. What is the single most important improvement My Ooredoo could make to enhance your experience?

Free text

Appendix 2 Operationalisation of the Constructs

Table A2.1 reproduces the operationalisation of the five reflective constructs of the structural model (Table 3 in the main text), enriched with the wording of each measurement item and the scales from which the items were adapted.

Table A2.1 :Operationalisation of the latent constructs, with item wording

Construct	Code	k	Item wording	Scale source
AI / Personalisation	AI	4	AI01 Suggests appropriate bundles based on usage habits; AI02 Understands my preferences and habits; AI03 Recommendations are relevant and useful; AI04 AI features changed how often I use the app	Komiak & Benbasat (2006); Pappas et al. (2017)
Chatbot Experience	BOT	9	BOT01 Understands requests; BOT02 Resolves without repetition; BOT03 Help at any hour; BOT04 Would reuse; BOT05 Improves quality perception; BOT06 Natural, conversational; BOT07 Smooth escalation; BOT08 More efficient than calling; BOT09 Overall satisfying	Chung et al. (2020); Ashfaq et al. (2020)
Navigation Efficiency	NAV	3	UX02 Minimal number of steps; UX03 Intuitive, effortless navigation; UX04 I do not feel lost or confused	Davis (1989); Hassenzahl & Tractinsky (2006)
UX Quality	UXQ	7	UX01 Overall UX satisfaction; UX05 Visually pleasant; UX06 Confidence in transactions; UX07 Pleasant, stress-free; UX08 Clear information; UX09 Feeling understood; UX10 Improves relationship with Ooredoo	Hassenzahl (2004); Lallemant et al. (2015)
User Loyalty	LOY	3	L01 Intend to continue using; L02 Would recommend; L03 Prefer over other channels / would not switch	Oliver (1999); Zeithaml et al. (1996)

Appendix 3: Expert Interview Guide

The following semi-structured guide framed the four expert interviews conducted between April and May 2026 (duration 20–55 minutes). It is organised around four thematic axes mapped onto the three research hypotheses, preceded by an informed-consent statement.

Introduction and consent

Thank you for your participation. This study examines how AI mechanisms shape user experience in telecom mobile applications; your expertise helps bridge theory and practice. Your participation is voluntary, your responses are anonymised in all publications arising from this research, and you may withdraw at any time. The interview is recorded with your consent.

Axis 1: Expert profile

Q1. What is your current role, and what is your professional experience with AI-driven UX, mobile applications, or customer-experience strategy?

Q2. What KPIs does your organisation track to validate the success of an AI-enhanced feature within a mobile application?

Axis 2 AI, navigational efficiency and perceived value (H1)

Q3. How does AI shift a mobile interface from reactive to anticipatory? Can you share a concrete example?

Q4. Have you observed a measurable link between AI-driven recommendations and reduced task-completion time?

Q5. How do you ensure personalisation adds value without becoming intrusive or confusing?

Axis 3: Chatbots, virtual assistants and UX quality (H2)

Q6. How significantly do chatbots improve service accessibility through availability and response speed?

Q7. What are the main barriers to natural conversational fluency in chatbots, and how are they being addressed?

Q8. How do you design chatbot personas to drive engagement without creating unrealistic user expectations?

Q9. What are the most critical chatbot failure points, and how do you manage escalation to human support?

Axis 4: Trust, control and perceived risk (H3)

Q10. How do you balance automation with the user's need for control? Does greater perceived control increase trust?

Q11. Should users always know when an algorithmic decision has been made? How does this transparency affect trust?

Q12. In your experience, what most commonly drives users away from an AI-driven app mistrust, wrong predictions, intrusiveness, or loss of control?

Closing

Q13. If you were redesigning the AI-driven UX of a telecom application from scratch, what single principle would you prioritise, and why?

We sincerely thank you for your time and insights.

Appendix 4: Qualitative Coding Procedure

The thematic analysis was conducted following Braun and Clarke's (2006) six-phase reflexive protocol. Three coding cycles were applied sequentially to the interview transcripts. Cycle 1 (open coding) generated 57 first-order codes through line-by-line reading. Cycle 2 (axial coding) grouped these into 19 second-order categories by identifying relational patterns and shared semantic fields. Cycle 3 (selective coding) integrated the second-order categories into six overarching themes (T1–T6). Every coding decision was recorded in a memo log as the audit trail required by the dependability criterion of Lincoln and Guba (1985). The full node hierarchy is reproduced in Table A4.1 below.

Table A4.1: Hierarchical node tree of the qualitative coding architecture

Parent theme	Sub-themes (condensed)
T1: AI as an anticipatory mechanism	Predictive personalisation, step compression, tailored promotion (counter-signal: maturity scepticism, E2)
T2: The personalisation paradox	Relevance–intrusiveness threshold, data minimisation, contextual intelligence, user control
T3: Chatbot ecosystem under constraint	24/7 availability, dialectal barrier (convergent finding, E3+E4), service integration, persona design, escalation, NLU robustness
T4: Trust architecture	Transparency (contested), user control as trust currency, the empathy gap
T5: Compound drivers of disengagement	Wrong predictions, loss of control, intrusiveness, cumulative mistrust
T6: Design-philosophy convergence	Simplicity-first, transparency-and-control, MVP discipline

Appendix 5: PLS-SEM Output

This appendix consolidates the key quantitative outputs of the PLS-SEM analysis. The structural model was specified in SmartPLS 4 and estimated through a Python implementation (numpy, pandas, scipy) with 5,000-resample bootstrapping and bias-corrected and accelerated (BCa) 95% confidence intervals, following Hair

et al. (2019). The full measurement and structural model (path diagram) is reproduced as Figure 29 in the main text (Section 2.6).

Table A5.1: Reliability and convergent validity of the measurement model

Construct	Code	k	Cronbach's α	CR (ρ_c)	AVE	$\sqrt{\text{AVE}}$
AI / Personalisation	AI	4	0.929	0.950	0.827	0.909
Chatbot Experience	BOT	9	0.958	0.965	0.754	0.868
Navigation Efficiency	NAV	3	0.855	0.912	0.775	0.880
UX Quality	UXQ	7	0.952	0.961	0.778	0.882
User Loyalty	LOY	3	0.889	0.931	0.819	0.905

Thresholds (Hair et al., 2019): Cronbach's $\alpha \geq 0.70$ acceptable, ≥ 0.90 excellent; $CR \geq 0.70$; $AVE \geq 0.50$. All constructs satisfy the reliability and convergent-validity criteria.

Table A5.2: Structural model: hypothesis-testing results (bootstrap B = 5,000, N = 163)

Hy p	Path	β	SE	t	p	95% BCa CI	f^2	R^2	Decision
H1	AI / Personalisation $\rightarrow$ Navigation Efficiency	0.545	0.074	7.36	< 0.001	[+0.376, +0.670]	0.423	0.297	Supported
H2	Chatbot Experience $\rightarrow$ UX Quality	0.398	0.097	4.10	< 0.001	[+0.195, +0.579]	0.160	0.453	Inconclusive
H3	AI / Personalisation $\rightarrow$ User Loyalty	0.587	0.089	6.63	< 0.001	[+0.403, +0.748]	0.305	0.441	Supported

β = standardised path coefficient; SE = bootstrap standard error; f^2 = Cohen's effect size (0.02 small, 0.15 medium, 0.35 large); R^2 = variance of the endogenous construct explained by its predictors. All three hypothesised paths are positive and significant at the 0.1% level; H1 and H3 are supported, while H2 is reported as inconclusive because the chatbot construct was measured from genuine experience for only a minority of respondents.

Appendix 6: Supporting Material

The figures below are screenshots of the My Ooredoo Algeria application (package com.algeria.selfcare.app.android), captured during the internship at Ooredoo Algeria with the authorisation of the Customer Value Management and Digital Care teams. They illustrate the visible AI and self-care touchpoints discussed in Chapter II.



Figure A6.1: Home dashboard: balance, active plan and usage summary.



Figure A6.2: “Personnalise mon forfait”: AI-assisted plan personalisation and special offers.



Figure A6.3: Detailed usage tracking (data, voice, validity).



Figure A6.4: Transaction and recharge history.

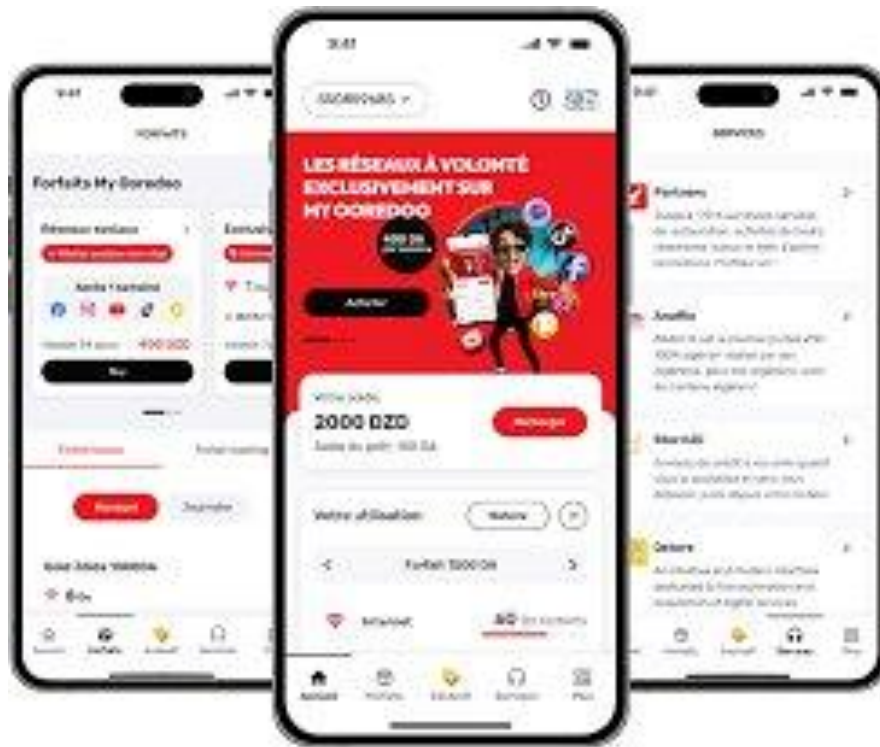


Figure A6.5 :Composite view: plans, dashboard and the Services menu (self-care entry points).

Additional supporting data :including the Google Play Store listing of the application and the operational details of Ooredoo Algeria's CVM machine-learning models and the Sprinklr conversational layer were collected with the authorisation of Ooredoo Algeria's Customer Value Management team. Due to confidentiality obligations, full reproduction is not possible; the relevant data is cited directly in the main text with the reference: “Internal interview, Customer Value Management team, Ooredoo Algeria, May 2026 (unpublished data, cited with the authorisation of the host organisation).”

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