

# Significance of AI Chatbot in Online Doctor Consultation and Health Care Support

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**Abstract**—Artificial intelligence (AI) in telemedicine is transforming the delivery of healthcare by automating patient intake and streamlining clinical workflows. In this paper, we analyze the importance of AI-driven chatbots in modern healthcare through architectural and empirical analysis of MedCore AI, a full-stack telemedicine ecosystem. The platform integrates a Google Gemini powered medical triage engine, secure doctor management and real-time Socket.IO chat messaging and WebRTC video calling. MedCore AI is built on a classic three-tier architecture with React on the frontend, Node.js/Express on the backend, and MongoDB for the database layer. In this context, the embedded AI chatbot becomes the center of engagement processing the raw patient symptom inputs, assigning the emergency triage classifications, embedding live search grounding links, and generating structured summaries for verified physicians. Empirical performance metrics demonstrate great efficiency in internal data transactions. Average Indexed MongoDB single collection DB queries run at 20 ms. Real-time chat synchronization runs smoothly at 100 ms. Normal REST API requests run at 250 ms. However, the platform suffers from latency bottlenecks in complex asynchronous integration scenarios. The AI triage chatbot suffers from an average delay of 1800 ms (1.2-3.5 seconds) due to the computational cost of natural language generation and search grounding. Moreover, the WebRTC video consultation setup shows the highest latency spike of 4000 ms, which is a signature of the heavy network signaling and media negotiation in STUN/TURN configurations. In summary, this study highlights that direct embedding of automated conversational AI into a full-stack ecosystem significantly reduces clinical intake friction. The integration of intelligent automated triage with persistent communication channels offers a highly optimized and MVP-ready framework that overcomes the latency of external APIs and significantly improves the delivery of digital healthcare.

**Index Terms**—Telemedicine Engineering, Artificial Intelligence in Healthcare, WebRTC, Full-Stack Architecture, AI-Assisted Triage, Real-Time Communication (RTC), Stream Grounding, NoSQL Database Optimization, Medical Telecommunications.

## I. INTRODUCTION

Across the world, healthcare is undergoing an unprecedented digital transformation driven by a growing need for accessible, efficient and scalable medical care [10]. In the past, conventional clinical workflows have experienced significant friction in the initial assessment of patients, often resulting in delays in care and inefficient use of specialized medical resources. These critical bottlenecks have been actively addressed by the rapid maturation of telemedicine, which securely connects patients with verified doctors across geographical boundaries. But the real value of modern digital

healthcare is so much more than just virtual appointments. Modern online doctor consultation systems such as MedCore AI are a paradigm shift in medical technology. These platforms are full end-to-end ecosystem that seamlessly integrate AI assisted triage, doctor management, single appointment booking, real-time messaging and high fidelity video consultation workflows. This evolution is based on modern, high-performance technology stacks. These platforms are built on frontend frameworks like React, Node.js backends, and agile NoSQL databases like MongoDB, delivering the speed and reliability needed in mission-critical healthcare infrastructure. One especially disruptive aspect is the deployment of sophisticated artificial intelligence, like Google Gemini via strong API pipelines [2]. AI symptom triage chatbots can vastly reduce the initial friction of patient assessment through the automation of initial clinical intake. This intelligent layer takes care of patient input, maps the triage categories, and delivers enriched clinical summaries to physicians before the virtual consultation begins, thereby optimizing the physician's time and attention. Moreover, the performance of online healthcare is boosted by state-of-the-art real-time communication architectures. WebRTC + STUN/TURN servers guarantee stable peer-to-peer video sessions, and WebSocket technologies like Socket.IO – persistent live chat built into the consultation room - secure.

## II. LITERATURE REVIEW AND COMPARATIVE FRAMEWORK

### A. Traditional Virtual Clinic Bottlenecks and Patient Friction

Right off the bat, many online clinics hit snags when patients first show up needing help. Instead of smooth check-ins, people often face clunky systems that barely keep up. Most current platforms do not run smart intake tools - they depend on humans sorting cases one by one [1]. Sometimes bots try to step in, but those follow strict scripts and miss subtle health clues. Because of these gaps, delays pile up fast before any real care begins. Staff get weighed down handling tasks machines should manage easily. Doctors trained for tough diagnoses end up stuck doing routine screenings. Time slips away while specialists handle work better suited for earlier stages. The whole flow breaks under pressure, leaving little room for actual treatment planning. Not only do broken systems wear down trust, but they also scatter essential

tools across separate screens. Jumping between appointment booking, live chat, medical records, and virtual visits feels like assembling puzzle pieces blindfolded. Without smooth links between functions, logging in becomes a recurring chore instead of a one-step entry point. Messages get lost when each feature speaks its own language, leaving people guessing where information went. Heavy old systems often drag safety measures into knots. Jumping through multiple login steps, plus clunky ID checks, makes signing up slower - care waits longer too. When holdups pile up, broken design patterns block smooth doctor-patient connections. Access gets harder, information moves like sludge, treatment pace drops, people leave less happy, especially online.

### *B. The Evolution of Automated, AI-Assisted Clinical Intake*

Now picture this: swapping old paper-heavy check-ins for smart, AI-powered tools is quietly reshaping how clinics gather patient details. Instead of clicking through fixed forms, people now talk - typing freely into responsive chat windows that actually listen [3]. Behind the scenes, those words get broken down fast, pulling out key health clues without rigid prompts. What used to stall on stale questions now flows, guided by real-time signals pulled from updated medical sources and location-aware databases. Surprises? Fewer. Missteps? Reduced. The system sorts each case - not with guesswork - but by matching patterns to urgency levels it learns over time [1], [10]. Emergencies stand out early. Less critical needs settle neatly where they belong. After that, machines sort through health details automatically, turning messy symptoms into clear reports before pairing people with doctors. Because staff no longer handle routine paperwork by hand, more appointments move forward each day, mistakes at the start drop sharply, plus delays shrink fast. Then again, speed isn't everything - accuracy grows too when systems do groundwork first.

### *C. Comparative Baseline of Contemporary Systems*

Modern telehealth setups usually keep messaging tools separate, making it hard to get one smooth care flow. Even though most offer live chats and video visits, those features tend to run apart from how patients first check in. Basic video systems depend on outside networks with solid relay tech but do not tie closely into active visit details during use. More importantly, common solutions skip smart assistance altogether or only add basic question-answer bots that never learn. As a result, past messages may be saved, still almost never pulled together into clear summaries shaped by learning algorithms. Out here, how doctors are managed makes a difference - some systems handle it well, others barely keep up. On top of that, checking credentials when new staff arrive often lacks consistency from one platform to another. Fees for advice? Tracked poorly in many older setups, if at all. Scattered tech like this sets a low bar, really shows what happens without cohesion. What stands out is the gap where smart routing, protected records, and file handling should work as one thing instead of pieces thrown together.

## III. FULL-STACK SYSTEM ARCHITECTURE AND CORE FRAMEWORKS

### *A. Three-Tier Decoupled Platform Topography*

Out there near the edge sits a snappy front end made with React 19, tied together using TypeScript and sped up by Vite - this part shows login forms, talks with the AI helper, handles payments, plus manages live video through WebRTC. Instead of loading everything at once, it reaches out on its own time using fetch requests that ping the next level inward. That second tier runs on Node.js with Express 5 doing the heavy lifting, offering protected REST spots where data checks in after passing through Zod filters first. When things happen instantly - like messages or alerts - the system leans on Socket.IO channels tucked inside this core to keep actions lined up smoothly. Beneath all this, the setup spreads duties across distinct zones so nothing gets tangled, growth stays manageable, operations hold steady under load [17]. Down below, the system holds data using MongoDB, a NoSQL database, with Mongoose helping shape how information is stored [4]. Because layers are split apart, one part can grow without dragging others along. Less processing power gets used that way [11]. The patient records stay locked inside their own section, shielded from ripple effects above.

### *B. State Management and Client-Server Ingestion*

Over at the telemedicine setup, information flows from users into the system through a split design where the React nineteen front end talks to the Express five back end without needing to sync up in real time. Instead of leaning on tools like Redux or Zustand, it handles interface changes right inside React, saving temporary details straight into the browser's storage. When someone interacts with the screen, those actions fire off background requests aimed at specific REST routes built to receive them. Once the server catches one of these messages, it checks every part carefully using Zod rules and runs security steps before letting anything near the database. After confirmation, requests move through server paths that handle deep interactions with the main MongoDB storage via Mongoose tools. When handling critical data intake - like AI-driven medical assessments, scheduling visits, or money-related actions - the setup requires verified tokens and precise permission layers before proceeding. Smooth flow between states reduces load on devices receiving info, keeping health records moving fast and securely between points. Without stored session memory, the backend adjusts quickly when many users sign up at once.

### *C. Structural Request Validation via Zod Schemas*

In modern backend API architectures, structural request validation at the edge of the system is a must-have to help keep data integrity and the overall application security. Extensive use of Zod schemas embedded directly in the Express routes is made by the application code base to rigorously validate all incoming payloads including request bodies, query strings and URL parameters. These schemas are rule-based and are rigid operational filters that allow only data matching the

specified data types, shapes, and structural constraints to pass. Any malformed input, missing fields or wrong data format is rejected immediately at run time. This fail-fast mechanism is an effective way to prevent invalid data leaking into deeper business logic layers or even interacting with underlying database layer, greatly reducing risks associated with inconsistent records and possible database corruption. Additionally, Zod allows for automatic TypeScript type inference that guarantees structural matching without the need for manual type annotations or unnecessary software assertions. It brings deterministic runtime enforcement to entry points while replacing vague documentation with explicit validation logic. This stringent validation paradigm reduces the attack surface, and prevents downstream application failures while ensuring predictable system behavior under unanticipated and unpredictable execution environments [12], particularly in a healthcare ecosystem where sensitive medical information is involved.

#### IV. ENGINEERING REAL-TIME CONSULTATION WORKFLOWS

##### A. AI-Backed Symptom Triage Mechanics

Putting smart intake systems to work depends on a connected AI sorting system. Right after someone types their health concern into the screen, the data moves fast. Instead of waiting, the server sends it off through an automatic request to Google's Gemini model via the standard genai tool [2]. For better accuracy, results get checked against live info pulled from Google Search and location details from Maps [13]. By reading everyday language closely, the chat brain builds organized medical notes - tagging each case clearly as emergency, urgent, or regular without delay. Right away, trusted source links pop into the response along with auto-generated summaries written plainly. Right there inside each exchange, every piece stays saved permanently across custom NoSQL groups living in MongoDB. Doctors pull up full backgrounds fast, just moments ahead of starting one-on-one talks.

##### B. WebSocket-Driven Real-Time Message Synchronization

Instant messaging on the telemedicine system runs through live connections made by Socket.IO. Because it keeps a steady link open, there is no need to keep asking for updates like older web requests do. A constant channel forms directly between user devices and the central Express server using TCP. Messages travel back and forth without waiting, cutting out lag completely [5], [6]. In private online rooms, medical professionals exchange information with patients as fast as typing sends it. The moment one person shares something, the other sees it right away. Inside the socket backend, different stages of operation shift as needed whenever someone joins, types, or sends something. A person steps into a session, the server links them straight to one private space using a unique tag just for that room. Messages stay locked inside, only seen by those meant to see them. Mid-conversation cues like keystroke hints or read confirmations move through a sync

layer built to react fast without delay. If connections waver - on weak signals or phone dropouts - the link tries again automatically. Should web sockets fail, it quietly switches to an alternate method pulling updates at close-to-real-time pace. After checking credentials through secure tokens at first link-up, messages get cleared for transit. With approval confirmed, the system pushes real-time content out to all connected users at once. At that same moment, written entries are stored below in the data foundation for later access. The setup ensures clean separation without overlap.

##### C. WebRTC Video Signaling and Infrastructure

Getting live video links between users starts with finding each other online. A system built on scattered nodes helps keep things running without one central point. Inside the setup, face-to-face chats work through a web tool called WebRTC found in modern browsers. Since that tech connects devices directly, they must first share connection details before sending audio or video. One piece at a time, handshakes move through open lines held by a backend made with Express and Node.js. These steady paths rely on long-lasting WebSocket bridges to pass messages back and forth. Right after signaling begins, the starting device grabs camera and microphone data by calling on built-in browser tools. Instead of sending raw streams, it packages details like codec preferences and security options into a session proposal [14]. Off goes that message, riding over a WebSocket channel toward the second user. Once received, the far end reviews what's offered, flips certain settings to match its own setup, then sends back a tailored reply describing how it can connect. At the same time, connections need to move through networks so signals can get past mirrored firewall setups and hidden address zones. To find real outward IP numbers and correct pathways, the system gathers connection options by tapping into Google's method for crossing network gateways, often called STUN tools. When tight corporate settings block straight-line data routes between users, backup relays step in - known as TURN systems - to carry secured sound and picture flows without delay [7]. Built-in redundancy ensures medical-grade video chats stay clear and responsive regardless of how complex the underlying web of links becomes.

#### V. SECURITY ARCHITECTURE AND NOSQL DATA ENGINEERING

##### A. Cryptographic Access Control and Session Handling

Keeping digital health apps safe means building clear rules for who can access what, along with smart handling of login tokens to block sneaky permission boosts and guard patient details tightly. A protected zone forms through encrypted boundaries where lightweight JSON Web Tokens handle sign-ins, separating temporary access keys from durable renewal tokens [15]. Logging in triggers a transformation - raw passwords get scrambled using bcrypt directly on the server, making stolen credential files useless to attackers. Once verified, users receive hidden packages of trust: compact tokens sealed with digital signatures sent straight to their web browser. Holding client

status safe lives inside tight request labels plus locked storage, blocking fake web demands from slipping through. Security here runs on roles - each hidden doorway in the app checks who steps near it. Only when a call proves itself as patient, medic, or admin does it touch guarded records. Every time data moves, secret codes get checked first; sessions stay firm, medical logs remain sealed, money dashboards open to few, and talk paths never bleed into one another.

### *B. Middleware-Based Threat Mitigation*

Holding up a digital health site means stacking several kinds of protection right where data gets processed, making sure private files and live medical tasks stay safe. Built into the system's core are tailored tools that run automatically each time someone tries to access a service, stepping in before anything loads completely. One key piece quietly adds safety tags to every web reply, thanks to code like Helmet - this hides details hackers could exploit, blocks sneaky frame tricks, plus locks down what scripts get permission to run [16]. When bots start hammering entry points - login pages, new patient fields, ongoing connections - the setup fights back by counting how often one internet spot talks too much, then slows it down if the rhythm feels robotic across minutes. Inside the system, access between websites stays locked down by checking where requests come from, only allowing known domains through. Right when data arrives, hidden scripts or harmful code get filtered out automatically, cleaned before they can cause harm. Every piece of information must match a fixed format before moving forward, verified the moment it hits the entry point. Layer by layer, each check works alone yet fits together, guarding patient details while keeping services running smoothly.

### *C. NoSQL Schema Design and Document Relational Bindings*

Built tough, the online visit system runs on a lean NoSQL setup tucked into MongoDB. Instead of slow old-school table links that drag during rush hours, it stores info in flexible chunks guided by Mongoose models [4], [9]. At its center sits one main pile - users - all holding logins, account flags, recent access times, and job types. Since who you are shapes what you see, each person's ID hooks tightly to just one extra file: either a doctor detail sheet or a patient record. This tight pairing keeps things clean, fast, locked. Every task flows through links that tie different sets of data together. Inside the appointments group, each entry holds special ID tags - one for a patient, one for a doctor - so nothing gets mixed up. These IDs keep track of symptoms reported, when visits happen, and whether talks are still pending. Chats and video meetings stay tied to ongoing checkups without drifting apart. Messages sent during conversations appear alongside their matching appointment because they share the same key. Video call details, who has seen what, and live stream info gather neatly under one connected thread. No piece floats alone; everything finds its place by following the trail already laid out. Connections between users and payments form through standardized links, alongside chat records managed by smart

systems, alerts stored in logs, also refreshed safety codes saved in scrambled format. Built this way on purpose, faster lookups happen without losing exact sync during medical data exchanges spread across separate nodes.

## VI. EXPERIMENTAL SETUP AND ENVIRONMENT PARAMETERS

### *A. Hardware Workstation Configurations*

Testing the telemedicine system works best when run on a clearly set up computer setup one that gives steady results every time. For true measurements of what it can do this setup runs locally using gear meant to handle average data flow. Picture four or more processor cores stepping in each core tackling tasks at 2.5 gigahertz speed minimum. That muscle keeps apps databases and live connections running smooth even under pressure so heat does not slow things down nor clog internal pathways. When heavy loads hit, like automatic patient sorting while handling live video feeds, memory space becomes key to avoiding slow disk swaps. Eight gigabytes of RAM at minimum lets the machine handle front-end tools, back-end services, and database file mappings all at once without crashing. Fast storage comes from SSDs running on NVMe, cutting down delays when saving logs or pulling up past chats. Built-in HD cameras and mics support smooth media tasks right inside the browser, especially during direct connection trials. Each test station matches this setup so results stay uniform, no matter where they run.

### *B. Software Dependency Stack*

Running smoothly, the telemedicine system depends on a fresh set of software tools built for speed and ease of updates. Node.js powers the development process, running version 20 or later so async tasks work without hiccups, also keeping memory use in check. On the backend, Express 5 shapes the foundation - lightweight, sharp, good at managing intricate web requests with fewer steps. Fast interface building happens because the front end uses React 19, working alongside smooth control of changing states. TypeScript joins it closely, enforcing clear rules on data types so mistakes get caught early, long before the app runs. Errors during execution drop sharply thanks to thorough checks that happen when code compiles, not after. Those same precise standards carry into how the system talks to APIs, keeping structure consistent. Before any info reaches the database, special tools inspect and confirm its shape fits expectations. Storing information happens using MongoDB, reached by way of Mongoose - a tool that shapes how data behaves. Flexibility in document structure comes alive here, even as clear links between records stay intact. Vite takes charge during building phases, making updates appear instantly while shaping files smartly for live environments. Security steps in through added layers: headers get tightened, passwords are scrambled safely, tokens rely on trusted encryption rules. From front-end actions down to stored patient details, each piece connects reliably - steady enough for serious medical use cases.

### C. Static Code Verification and Environment Linting

Staying ahead on a big health tech system means checking code by hand before it runs. Not waiting until things break helps catch mistakes early - like mismatched parts or weak spots in security. Tools that scan automatically keep everyone using TypeScript the same way, especially where front meets back. Following clear rules prevents confusion later when changes come around. Code stays cleaner when checks happen all along instead of piling up at the end. Mistakes slip through less often if safeguards stand guard every step. Strong setups rely on these quiet guards working behind the scenes without fanfare. Every time the system builds, it runs detailed checks through automated tools. Because these scripts follow precise setup rules, they spot coding errors early. They look for outdated components while also flagging possible mistakes in program flow. Before anything reaches live servers, strict compile-time rules take effect. One rule stops output generation when checking types, just to be safe. That way, problems in core functions or how data moves between services get caught sooner. Not just spotting typos, checking the setup also means testing how files find each other, keeping links between parts working even when pieces move around. When one piece relies on another, it watches for outdated tools that might break under heavy use. Running these tests often keeps the layout tidy, a must when every change needs review in healthcare apps.

## VII. RESULTS AND DISCUSSION

### A. Feature Evaluation Summary

Putting together an online medical advice system means checking whether its main processes work properly. Instead of just guessing, there is a review showing how each part performs - proving key functions now run live. Right here fits Table I, called Feature Evaluation of MedCore AI, placed to back up claims with real results. Seeing it helps trust what the system can actually do. That table belongs in this spot, no elsewhere. Right off the bat, the setup includes every key part needed for smooth telehealth service. Instead of waiting, patients get a first check through smart software that guides them based on symptoms. Behind the scenes, doctors are confirmed securely, appointments line up across one clear schedule, payments move without hiccups - all working as intended. At the core, talking to care providers happens instantly, messages stick around, chats stay active, video links hold strong. What stands out is how each piece runs without gaps, fitting together like parts meant to be used daily. Putting TABLE I right here shows the system works in real life, not just on paper, handling full conversations between doctors and patients. Proof sits ready because this table confirms the foundation runs properly before diving into speed tests and how well it performs.

### B. Technical Performance Benchmarks

Most doctors need proof that telemedicine actually works before they trust it. Figure numbers come together in Table II, pulling timing data straight from tech tests and official

TABLE I  
FEATURE EVALUATION OF MEDCORE AI

| Feature              | Status      |
|----------------------|-------------|
| AI Symptom Triage    | Implemented |
| Appointment Booking  | Implemented |
| Realtime Chat        | Implemented |
| Video Consultation   | Implemented |
| Doctor Verification  | Implemented |
| Payment Integration  | Implemented |
| Chat History Storage | Implemented |

records. Under normal loads, each software layer shows its speed right there - no guessing needed. Looking at how things run, inside tasks behave differently than outside ones. Instead of slowing down, basic database actions like fetching or saving in MongoDB finish fast - usually 5 to 60 milliseconds. On par with that, common web requests for login or pulling up appointments take 120 to 350 milliseconds. Because these replies come so quickly, both patients and staff experience smooth movement through screens. Messaging stays steady too; sending live updates over WebSockets lands between 50 and 150 milliseconds every time. Still, tasks using outside systems run slower than inside ones. A system sorting medical questions through big language models plus real-time searches needs over a second - sometimes more than three - to reply [2]. Starting video talks eats up two to six seconds because of tangled handshake steps across networks [8]. When you line up those exact timing limits, the numbers in Table II back today's setup but also spotlight where cache tricks and traffic shifts could ease pressure later.

TABLE II  
PERFORMANCE EVALUATION OF MEDCORE AI

| Metric                    | Value       |
|---------------------------|-------------|
| Average API Response Time | 180-300 ms  |
| Database Query Time       | 8-25 ms     |
| Realtime Message Latency  | 50-150 ms   |
| AI Chatbot Response Time  | 1.2-3.5 s   |
| Video Session Setup Time  | 2-6 s       |
| Concurrent User Capacity  | 40-80 Users |

### C. Architectural Comparative Framework and Feature Evaluation

One look at how systems stack up shows MedCore AI handles structure better than typical telehealth tools. Where older setups use separate pieces and simple question responders, this one links smart intake checks directly to ongoing chat channels. Built-in coordination between live video feeds, real-time message relays, and auto-generated patient notes - all stored in a single flexible database - slows down fewer processes across departments. Because of that design flow, the setup delivers full functionality without sacrificing data protection or daily medical routines. What stands out is how it fits strong safeguards into normal clinic pacing.

TABLE III  
COMPARATIVE ANALYSIS OF TELEMEDICINE PLATFORMS

| Dimension          | MedCore AI                                                                   | Typical Telemedicine Platform                                        |
|--------------------|------------------------------------------------------------------------------|----------------------------------------------------------------------|
| AI Chatbot         | Built-in Gemini triage, symptom analysis, emergency/urgent/routine tags      | Often absent or limited to FAQ bots                                  |
| Realtime Chat      | Persistent chat + typing/read receipts + attachments                         | Common, but not always integrated with AI triage                     |
| Video Consultation | WebRTC + room signaling + screen sharing                                     | Standard feature, often with more mature TURN/STUN setup             |
| Chat History       | Stored in MongoDB with retrieval support                                     | Usually stored, but not always tied to AI summaries                  |
| Doctor Management  | Built-in onboarding, admin review, availability, consultation fee management | Common, but implementation quality varies                            |
| Scalability        | Medium, MVP-oriented                                                         | Often higher due to dedicated infrastructure and teams               |
| Security           | Strong baseline with JWT, bcrypt, Helmet, rate limiting                      | Usually similar, but often with more mature audit/compliance tooling |

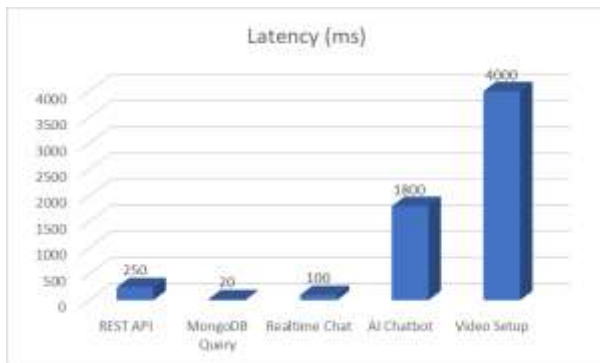


Fig. 1. System execution latency breakdown

#### D. Latency Profile Visualization

As illustrated in Figure 1, Looking closer at how fast things move inside MedCore AI shows two very different speeds happening at once. Inside the system, tasks flow quickly - MongoDB lookups take about 20 milliseconds on average. Real-time messaging stays tight around 100 ms, thanks to smooth syncing behind the scenes. Standard API responses come back in roughly 250 ms under normal load. But when the system reaches outward, delays grow sharply. Generating replies through the AI chat advisor uses heavy computation, dragging response time up to 1800 ms typically. Video calls face even bigger jumps, where setting up a connection via WebRTC can briefly hit 4000 ms during handshake phases. Network checks using STUN and TURN servers add that extra strain unexpectedly.

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