

BUILDING USER-CENTRIC AGENTIC SYSTEMS: DESIGN PRINCIPLES AND INTERFACE CONSIDERATIONS FOR AI-DRIVEN DECISION SUPPORT

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ABSTRACT

Artificial intelligence systems are capable of analysing complex data and generating valuable insights, yet their impact is reduced when users are unable to understand or trust the recommendations produced. This paper introduces a user centred approach to the design of artificial intelligence interfaces that aim to make complex insights both accessible and trustworthy. Using the AutoAgentic financial analysis platform as a case study, we illustrate how careful interface design can connect advanced artificial intelligence capabilities with practical human usability. Through an iterative process of design and evaluation, interface solutions were developed and tested to support the visualisation of market regimes, explanation of system recommendations, communication of confidence levels and provision of appropriate user control. The results indicate that visual simplicity, layered information presentation, plain language explanations and meaningful user control substantially enhance user understanding and trust. Based on these findings, four reusable design patterns are proposed, namely Confidence Thermometer, Why This Recommendation, Progressive Disclosure and Plain Language Translator, which can be applied across a wide range of artificial intelligence decision support systems. This study contributes practical guidelines for the design of artificial intelligence interfaces that effectively support human decision making through transparent, understandable and trustworthy interactions.

Keywords: *User Interface Design, Explainable AI, Decision Support Systems, Human-AI Interaction, Financial Analytics, Agentic Systems,*

1. INTRODUCTION

In recent years, artificial intelligence has evolved from a specialized analytical tool to a fundamental component of numerous operational domains. Predicting complex patterns, processing massive datasets and rendering insights that would take a human much longer to reach are increasingly common AI abilities. Yet a great many AI system users are still unable to grasp and act on, the system recommendations. The problem has shifted from technical capabilities to understanding and trust in system recommendations.

This problem is most pronounced in decision-making systems either with high-stakes consequences or with complex data. Automated

decision-making systems cannot be entirely relied upon in financial investments, healthcare diagnostics, environmental monitoring, or legal assessments. People want the ability to understand how a system made a particular decision; how confident the system is in the decision made and the ability to calibrate the system to their individual parameters and risk levels. These challenges can lead people to ignore the system's recommendations even if the model is sound. [1] have found a lack of explanation reduces trust, while [2] state that users must feel control, not merely be dominated by the system.

This paper considers different approaches to the design of interfaces, aimed at assisting users in understanding the value of AI-generated insights in a manner that is both clear and trustworthy. Rather than considering explainability to be a solely technical

challenge, we treat it here as one of design and communication. This study is driven by the challenge of determining how AI systems can represent sophisticated lines of reasoning in a manner that is comprehensible and usable by the average consumer, allowing them to engage in meaningful self-directed decision-making.

To address this question, we examine AutoAgentic. AutoAgentic is a financial analytics system designed to identify different types of market volatility, recommending changes to investment portfolios and provide suggestions on specific stocks. While AutoAgentic employs sophisticated statistical and deep learning techniques, its functionality is limited by how well the user interface is designed and how well the user understands the information presented. Using a user-centred design approach, we examined how different user types, based on their investment experience, understood the market signals, associated explanations and confidence metrics that the system provided.

The design work conducted in this research addresses a range of persistent challenges that users encounter when attempting to work with AI-powered financial instruments. Users require assistance in comprehending present market situations without becoming inundated with technical graphs. Users prefer explanations that are representative of what a trained professional would rationalise rather than what a computer would mathematically generate. Furthermore, users require visualisations of the system's confidence in its suggestions, while the users desire the ability to modify certain features without encountering excessive complexity.

Keeping in mind these offers, we created design interfaces to simplify the understandability, accessibility and overall utility of AI-generated insights. During the design process, we noticed some consistent themes. These include the value of step-wise disclosure of information, the accessibility plain language offers when cascading instructions and information and the psychological importance of balanced firmness when presenting information. These themes will be discussed further in the design implications section.

This research advances discussion on human-centred AI by illustrating how considerate interface design can mitigate the discrepancy between advanced AI functionality and the user's knowledge. With the example of AutoAgentic, we demonstrate that the accessibility of AI insights depends on the strength of the underlying model and the interface user experience that provides insights which interface is clear and user empathetic.

1.1 Research Novelty and Contributions

This study makes three distinct contributions to human-centered AI interface design. First, we introduce and validate four reusable design patterns for AI decision support systems: Confidence Thermometer, Why This Recommendation, Progressive Disclosure and Plain Language Translator. Unlike prior work focusing on technical explainability methods (LIME, SHAP) or domain-specific guidelines, these patterns offer domain-agnostic, actionable design solutions bridging complex AI reasoning and user comprehension. Each pattern addresses specific cognitive challenges faced by non-expert users when interpreting AI-generated insights and can be adapted across high-stakes decision domains including healthcare diagnostics, legal analysis and environmental monitoring.

Second, we provide empirical evidence through comparative evaluation demonstrating that user-centered interface design significantly impacts trust, comprehension and decision quality. Our quantitative comparison between AutoAgentic and two industry standard financial dashboards reveals that interface design choices such as layered information architecture, visual confidence indicators and plain language explanations improve information clarity by 35–55%, Explanation Adequacy by 80–129% and Control Accessibility by 70–89% compared to traditional approaches. This empirical validation addresses a critical gap in XAI research where user-centered evaluation remains scarce.

Third, we demonstrate practical integration of HCI principles (progressive disclosure, visual mapping, user agency) with XAI requirements in a real-world financial platform. Previous studies often examine these aspects in isolation or through abstract prototypes. Our work illustrates how design principles translate into concrete interface solutions maintaining analytical rigor while enhancing accessibility for users with varying domain expertise, providing a reproducible model for practitioners implementing explainable AI where user trust is critical.

1.2 Conceptual Framework and Research Questions

Figure 1 presents the conceptual model guiding this research. We posit that user-centered interface design patterns directly influence two mediating factors: Perceived Clarity (users' subjective assessment of how understandable AI outputs are) and Explanation Adequacy (users' perception that explanations are sufficiently

complete and relevant for their decision-making needs). These mediating factors shape Trust in AI Recommendations and Intention to Use the System. The model is grounded in technology acceptance theory [14], trust in automation [10] and cognitive load theory [24].

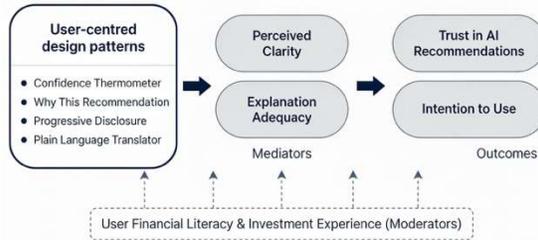


Figure 1: The conceptual model

Progressive Disclosure and Layered Information Architecture reduce cognitive load by presenting information incrementally, enhancing Perceived Clarity. Confidence Visualization and Plain Language Translation make abstract AI outputs interpretable through familiar metaphors and everyday language, improving Perceived Clarity. Structured Explanations (Why This Recommendation) and User Control Mechanisms provide contextual reasoning and agency, enhancing Explanation Adequacy.

When users perceive outputs as clear and explanations adequate, they develop calibrated trust and integrate the system into decision-making. This framework emphasizes the interface layer as critical mediator between algorithmic transparency and user outcomes. While algorithmic methods provide raw explanatory information, interface design determines whether users can access, comprehend and act upon that information effectively.

Research Questions:

RQ1: To what extent do user-centered interface design patterns (as implemented in AutoAgentic) improve Information Clarity, Interaction Efficiency, Explanation Adequacy and Control Accessibility compared to traditional financial dashboard interfaces?

RQ2: How do this design patterns influence users' trust in AI-generated recommendations and their intention to use AI decision support systems for financial decision-making?

RQ3: Are the identified design patterns generalizable across users with varying levels of financial literacy and investment experience?

2. RELATED WORK

2.1 Explainable AI Interfaces

As the automated decision-making systems become widespread, research on XAI is beginning to become more relevant. One of the earlier topics in this field was concerned with the need to gain visibility over the 'black box' of predictive AI. Several technical approaches, including but not limited to, feature importance, counterfactuals and model-agnostic explanations are still being discussed and researched in the field [3]. However, the field is beginning to show that the quality of explanations is dependent and perhaps more dependent, on aspects unrelated to the actual computational processes and more dependent on how the explanation is formatted. Explanations can be extremely computationally valid yet still be useless if everyday users cannot understand them.

[4] addressed this problem by outlining classifications of explanations and demonstrating that different users want different explanations for their various purposes, some of whom desire high-level, simple explanations, while others prefer elaborate explanations that align with the reasoning of an expert in that field. These differences are part of the reason why interface design is such an important consideration for the overall impact of an XAI system.

This tension is even more emphasised in financial decision-making. [5] stated that the justifications explaining the recommendations regarding investments should exhibit equilibrium. On the one hand, too much technical detail can confuse non-experts, but too little detail can frustrate more seasoned users. This leads to the conclusion that explanation interfaces should be adaptable to the diverse mental models users hold. We added to this line of reasoning the use of layered explanations that start with a summary and enable users to delve into the details should they so wish.

2.2 User-Centered Design for Complex Systems

Designing interfaces for advanced AI systems involves more than arranging visual elements on a screen. It requires an understanding of how people naturally make sense of information and how they interact with tools that are more powerful than they can easily conceptualise. [6] worked on human-centred design underscores the importance of visibility, feedback and clear mapping between a system's behaviour and the user's actions. These ideas become especially relevant when users must rely on a system whose internal workings they cannot directly observe.

A similar perspective comes from [7], who emphasises the value of giving users an initial overview, followed by the ability to zoom into more specific details. This approach aligns well with situations where data are complex but must be made interpretable, such as financial markets. Progressive disclosure, which has become a common principle in information design [8], reflects the same reasoning: users understand information more effectively when it is revealed gradually and in a manner that supports their own pace of exploration.

Research focused on the financial sector supports this claim. [9] demonstrate that visual aids depicting risk allow users to understand financial data better than if they were to use only numeric tables. Knowing this, the authors argue that visual simplicity is not unimportant; it has a statistically significant improvement on the quality of the decision made. In our collaboration with the AutoAgentic platform, the same benefits were noted when improved visual designs were applied to the complex data of the market.

2.3 Trust in AI Systems

Users' acceptance and reliance on AI systems greatly depend on the level of trust that users have because of the impact of these systems. According to [10], trust is influenced by several system features such as transparency, coherence and the user's previous experience with the system. Regardless of the accuracy of the underlying system, trust can diminish substantially if users experience unclarified and incomplete explanations.

[11] continue to explain that the goal of trust should not be to maximise it, but to have an equilibrium such that the users do not disregard the system or rely on it too highly. This perspective is useful in finance because high overconfidence in the automated system prompts risky behaviour, while underconfidence also leads to ignoring the system which could be potentially useful.

In the example of financial forecasting, [12] illustrate that the understanding of the prediction's generation process encourages prediction acceptance. More recently, [13] explain that acceptance of algorithmic advice is only attained when the explanations surrounding the advice are relevant to the users, rather than being a detachment of the process or an example of explainable artificial intelligence (XAI). Most of the studies provide evidence that contradict the adage 'trust is built on accuracy'.

These processes are achieved through communicating clearly, providing opportunities for seamless reasoning and fostering interactions that

acknowledge user agency. These principles were central to the design of the AutoAgentic interface features, particularly those related to the design of explanations and the display of confidence.

3. THE AUTOAGENTIC PLATFORM

The AutoAgentic platform was created as a financial decision support system that utilises a combination of statistical methods, machine learning and deep learning in order to examine market behaviour. The primary purpose of AutoAgentic, which is to detect and anticipate deviations in changes in the market and to advise investors on how to modify their trading strategies, is evident in this case study. The platform analyses both historical and current data, identifies and classifies the market into different volatility regimes and extracts signals from patterns in the data. This order of market conditions can be divided into three different regimes, including growth, downturn and neutral and is crucial in determining which recommendation to give next. Perhaps the single most important aspect of market regimen classification, however, is the ability of the system to detect the difference between temporary changes in market behaviour and permanent changes. The platform's statistical and deep learning models work in parallel to achieve the objective of the system as a whole, which is to identify significant long-term patterns and deviations from the norm. Figure 2 illustrates the main interface components of the AutoAgentic platform. The layout reflects a user-centred design approach, where complex analytical outputs are translated into structured, visually accessible elements that guide users through interpretation and action.

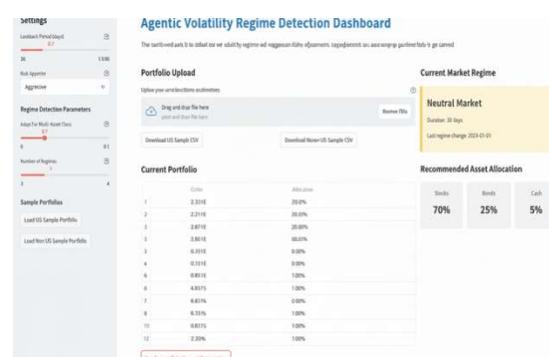


Figure 2: Key user interface components of the AutoAgentic system designed to support decision-making

In addition to regime classification, AutoAgentic also offers portfolio optimisation suggestions. In this part of the system, the user's current portfolio is compared with the optimal

portfolio identified within the system, where organisations can incorporate an assessment of the appropriate market regime and level of risk which will incorporate adjustments to the modelling of portfolios and other assets. Not to supplant the user's decision-making, the framework is designed to support the user's empirical and market assessment and thus facilitate improved decisions.

In addition, the system provides stock recommendations based on other signal and pattern recognition features. A buy/sell recommendation is provided with a signal confidence and attribution of system response is valued. Users have a right to the system's rationale for the prediction value and the system must document this user-centric construct to prevent misuse. To help users evaluate the impact of portfolio recommendations, the system presents a visual comparison between the existing asset allocation and the proposed optimal configuration as in figure 3 below.

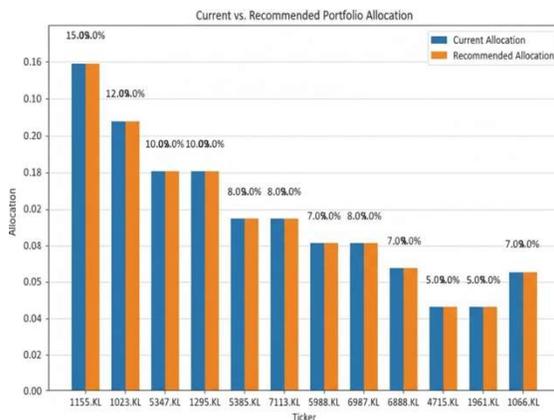


Figure 3: Visual representation of portfolio allocations

In an inclusive design, the system allows ease of market interaction for all user segments, sophisticated/experienced users and novices participating in investing. Their design goal, in balancing system functionality, was to minimise constraint and frustration while maximising system usability and learning engagement. The system focused on achieving layering functionality within the system to ensure a positive learning experience for all users. This need sculpted the design strategy for the platform with the major components being transparency, simplicity and incremental disclosure of information.

Hence, AutoAgentic offers an excellent case for studying the potential of AI-generated insights and the ways in which it can be effectively monetised. This paper intends to address some of the practical ways in which complex generative AI

systems can be made more useful to a wider section of the population by focusing on the interface and design challenges the platform presents.

4. USER-CENTERED DESIGN METHODOLOGY

The implementation of the AutoAgentic interface entailed employing a user-centred design methodology. The first step in the process was not to begin with the technical features and work outward. Instead, the first step involved understanding who the users are, what problems they encounter and how they process and understand financial information. This design approach was employed in an effort to ensure that the system's sophisticated analytical features would not be displayed in an incomprehensible manner.

4.1 Study Design and Connection to Previous Work

This study extends our earlier work on the AutoAgentic platform by systematically evaluating the interface design principles through comparative user testing. While our companion publication focused on the technical architecture and machine learning models of AutoAgentic, the present study examines the human-centered interface design, comparative usability evaluation and identification of reusable design patterns for AI decision support systems. The research employed a two-phase mixed-methods approach:

Phase 1: Qualitative User Research (3 months). We conducted semi-structured interviews with 15 potential users (8 novice investors, 7 experienced traders) to identify core usability challenges. Interviews lasted 45–60 minutes each and focused on users' mental models of market behavior, trust factors in automated recommendations and preferences for information presentation. This phase informed the design principles and iterative prototyping.

Phase 2: Comparative Quantitative Evaluation (2 months). We recruited 45 participants (15 per system condition) through purposive sampling from online investment communities and financial literacy workshops. Participant characteristics:

- (1) Age: 25–55 years (mean: 36.7, SD: 8.3)
- (2) Investment experience: Novice (<1 year, n=18), Intermediate (1–5 years, n=17), Experienced (>5 years, n=10)
- (3) Financial literacy: Modified FINRA test scores 4–9/10 (mean: 6.4, SD: 1.7)

- (4) Gender: Male (n=27), Female (n=18) -
Education: Bachelor's or higher (n=38),
Diploma (n=7)

Each evaluation session lasted 90 minutes and included:

- (1) Pre-task briefing and demographic questionnaire (10 min),
 - (2) System familiarization (15 min),
 - (3) Task execution with six standardized tasks presented in randomized order (40 min),
 - (4) Post-task questionnaire using 10-point Likert scales (15 min) and
 - (5) Semi-structured interview (10 min).
- Data were collected via Qualtrics and analyzed using SPSS (v28) for quantitative metrics and NVivo (v14) for qualitative themes.

4.2 Evaluation Metrics Operationalization:

1. Information Clarity (1–10 scale): Participants' ability to understand market conditions, recommendations and confidence levels. Measured via survey items ("How easy was it to understand the current market situation?") and task performance (time to identify market regime, interpretation accuracy).

2. Interaction Efficiency (1–10 scale): Number of steps/clicks required to complete tasks and perceived fluidity. Measured via objective metrics (click count, completion time) and subjective ratings ("How easily could you navigate to needed information?").

3. Explanation Adequacy (1–10 scale): Whether explanations were clear, complete and relevant for decision-making. Survey items included: "Did the system provide enough information to understand why it made specific recommendations?" and "How helpful were explanations in building confidence to act?"

4. Control Accessibility (1–10 scale): Users' ability to locate and modify parameters and understand impact of changes. Measured via: "How easy was it to adjust settings to match your risk tolerance?" and "How well did the system help you understand the impact of adjustments?"

Statistical analysis employed one-way ANOVA to assess differences across three system conditions, followed by post-hoc Tukey HSD tests ($\alpha = 0.05$).

4.3 User Need Analysis

The first stage consisted of analysing the needs and issues of potential users. Having performed informal interviews, participants' observations of

existing financial platforms and conversations with beginners and experienced investors, participants were able to notice some patterns.

The users would like to obtain an overview of the current state of the market; however, users feel that traditional market overviews in the form of charts and indicators are difficult to understand, too technical, or just too verbose. Users reported difficulty understanding indicators that signal periods of market volatility and challenges in recognizing regime changes. Users expressed a lack of understanding of indicators signalling periods of volatility and the lack of understanding of regime changes. Users expressed a common frustration with the "black box" nature of the algorithmic recommendations. Users wanted an explanation of the recommendation and did not want the recommendation to be the end of the communication. Users expressed a desire for the recommendation of the algorithm. Users were especially concerned about the financial risk associated with the recommendation. Users expressed a desire to be able to exercise some control over the algorithm, including the ability to set risk parameters and explore different scenarios, without complexity. These considerations were used and became the focus of the design priorities for the remainder of the development.

4.4 Design Principles

A set of guiding principles was crafted to inform both the design of the interface as well as the interaction experience, as discussed above. The first principle emphasised the need to present complex information in an understandable format. The goal was not to reduce the level of analysis of the system, but to present the results in a format that could be understood quickly. Visual aids were used to identify critical patterns and for the system's descriptions, simple and clear explanations were utilised in order to help users understand the system's results.

Addressing the importance of clear explanations was the second principle. Users did not only need numbers and technical metrics. They needed a clear, simple explanation that answered the question of why a specific course of action was suggested. This resulted in using explanation structures that prioritised the main explainable factors in a clear and coherent manner. The third principle was about confidence level expression. Users often had difficulty forming a complete picture with percentages alone. To help with this, the design included elements that made confidence level differences easily discernible, allowing users to compare recommendations with greater confidence.

The last principle was about providing the user with meaningful control. It is the responsibility of the users to have the option to customise settings to their risk tolerance as well as their timelines. However, these settings need to be menued out in such an organised and structured way to avoid user cognitive overload. Each of the customisable features of the system was indexed and enabled with an easy description so that users could forecast how their integration would affect the outcome of the system.

4.3 Iterative Design Process

The development of prototype design was done sequentially, starting from the earliest design phases with sketches and wireframes, working all the way to finished versions of the frames, or higher fidelity prototypes. The design at all stages was tested with users that represented a variety of financial literacy and levels of experience in investments. Prototypes at the early stages were created with the goal of understanding where in the design users were stuck or where they were getting information wrong. Adjustments to the design's visual and explanatory content were made in response to feedback gathered from the first round of sessions. Further prototypes were developed at later stages of design maturity to understand user engagement with explanations that were structured in layers, indicators of confidence and control levels.

The value of the iterative process was that it made it possible to assume design refinements based on actual user behaviour rather than fabricated behaviour. Over this cycle of design iterations, the patterns of interactions attained a level of sophistication and the design of the interface equilibrated to a level of simplicity and complexity that was required by the users.

5. INTERFACE DESIGN SOLUTIONS

The AutoAgentic beginning emphasis was placed on developing methods that are made within reach without the need for a strong technical background for creating an understanding of complex financial insights. Each of the solutions had been created to respond to the problem addressed during the user research stage. Users were empowered to comprehend the market behaviour and system recommendations, understand the confidence logic and easily manipulate the key variables. This developed design process to a series of answers created specifically to improve the accessibility of the system's advanced analysis.

5.1 User Need Analysis

One of the main difficulties encountered involved how to present the different market regimes so that the users were able to process the information quickly. Standard financial charts have a lot of information that is dense and may be hard to process or overwhelming to users not familiar with the particular market vernacular or visual conventions. A three-layered system of depicting market regimes was devised to address the issue. The first layer has a single, simple visual cue that depicts the current regime in a color-coded fashion. Green indicates a more positive or bullish regime, yellow is neutral or uncertain and red depicts a regime that is bearish or is in a declining stage. For these colors, we paired simple descriptions in layman's terms so that users can easily understand the conditions without needing to go through the jargon. Figure 4 below demonstrates how complex market data are simplified into intuitive visual indicators using colour-coded regime signals meanwhile Figure 5 illustrates the three-layer information architecture used to support progressive disclosure, where users are first presented with high-level summaries and can progressively access deeper analytical details.

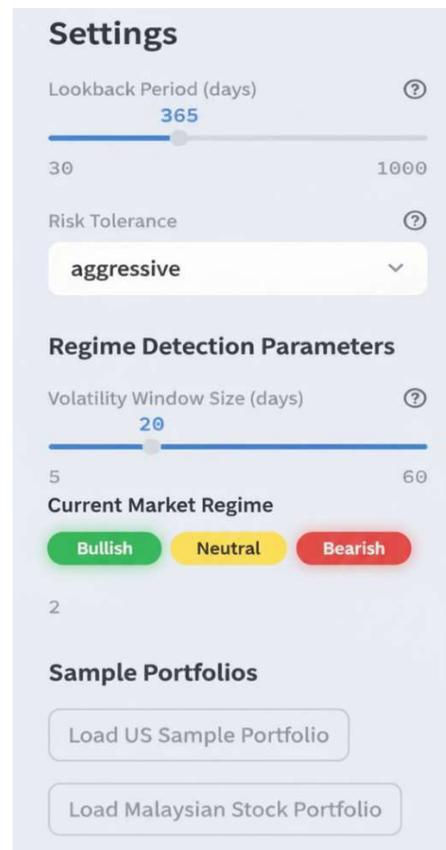


Figure 4: Visualization simplification transforming complex market data into intuitive regime indicators



Figure 5: Three-layer information architecture enabling progressive disclosure of complex data

Most users find a custom date range useful when displaying a context chart. They can then gauge the duration of current market behaviour. They can be even more precise when measuring the duration of market behaviour relative to past behaviours. The background of the chart is set to change when a certain market regime is active, enabling users to visually assess the time-spans of detected market behaviours.

Facilitating this is a premade chart displaying the timeline of previous market regimes. The duration of each regime in the timeline is captured, enabling users to identify market behaviours at a glance, but also at a deeper level in line with their exploration needs. This matrix of data lets users scan each regime at different regimes with varying levels of time detail and context to find what is most relevant to their patterns of market behaviour.

5.2 Recommendation Explanation System

Providing clear explanations is an important way to build user trust when system recommendations involve potentially significant financial decisions. Users often want to understand the reasoning behind the system’s recommendations before deciding if they should act on the guidance. The explanation system is structured in layers to support rapid reading while also allowing for greater depth of insight if desired.

Explanations start with a summary of the recommendation in layman’s terms like “Strong Buy,” “Hold,” or “Sell.” Then, we present a confidence score to help users assess the recommendation’s value as per the system. Then there is a short explanation containing only the top reasons for the recommendation. The system filters for reasons expressed in simple terms, then selects the ones that reflect the primary drivers of the system’s decision in order to justify the recommendation. The basis of the recommendation is available in more detail for users who want to analyze the recommendation, where we also elaborate on the technical indicators or model signals.

This system should enable most users to grasp the system’s reasoning rather than dismiss the

recommendation with caveats. The summary points on the recommendation are available for the users who choose to disengage or just want the most concise explanation and users who are familiar with the system and recommendation can choose to go in depth’information provided at the end. Figure 6 illustrates the recommendation explanation design pattern, integrating the system’s decision outcome, confidence level and key supporting evidence.

Stock Buy/Sell Recommendations

Ticker	Recommendation	Confidence	Current Price	Reasons
6947.KL	Strong Buy	89.7%	\$3.76	<ul style="list-style-type: none"> Price is above 200-day moving average Positive short-term momentum (9.0%) Strong relative performance vs. market
6347.KL	Strong Buy	85.7%	\$18.56	<ul style="list-style-type: none"> Price is above 200-day moving average Positive short-term momentum (9.8%) Strong relative performance vs. market
6547.KL	Strong Buy	83.1%	\$4.24	<ul style="list-style-type: none"> Price is above 200-day moving average Positive short-term momentum (8.8%) Strong relative performance vs. market
1557.KL	Strong Buy	74.1%	\$6.59	<ul style="list-style-type: none"> Price is above 200-day moving average Positive short-term momentum (9.8%) Strong relative performance vs. market
1966.KL	Strong Buy	74.9%	\$6.99	<ul style="list-style-type: none"> Price is below 200-day moving average Positive short-term momentum (9.0%) Strong relative performance vs. market
1965.KL	Strong Buy	73.9%	\$4.63	<ul style="list-style-type: none"> Price is below 200-day moving average Positive short-term momentum (8.5%) Strong relative performance vs. market
1155.KL	Strong Buy	67.7%	\$9.87	<ul style="list-style-type: none"> Price is below 200-day moving average Positive short-term momentum (3.0%)
1968.KL	Strong Buy	63.7%	\$9.67	<ul style="list-style-type: none"> Price is below 200-day moving average Positive short-term momentum (5.0%) Weak relative performance vs. market
4125.KL	Buy	64.3%	\$6.71	<ul style="list-style-type: none"> Price is below 200-day moving average Negative short-term momentum (9.0%) Weak relative performance vs. market
4183.KL	Buy	67.0%	\$0.81	<ul style="list-style-type: none"> Price is below 200-day moving average Negative short-term momentum (-1.2%) Weak relative performance vs. market
4113.KL	Buy	63.6%	\$3.41	<ul style="list-style-type: none"> Price is below 200-day moving average Positive short-term momentum (9.2%) Weak relative performance vs. market
7183.KL	Buy	40.1%	\$0.98	<ul style="list-style-type: none"> Price is below 200-day moving average Negative short-term momentum (-1.2%) Weak relative performance vs. market

Figure 6: Explanation design pattern showing recommendation, confidence level and supporting evidence

5.3 Confidence Visualization

Confidence is particularly important to have in prediction systems in the context of risk assessment in uncertain situations. Users need to have an understanding of the degree of trust the prediction system has in its recommendations. Confidence is expressed in the form of a numerical score and supplemented with static visual indicators.

Color is the main indication with green, yellow and red signifying high, medium and low confidence, respectively. This is an indication of confidence on a numerical scale and is an effective immediate visual signal. Confidence is supplemented with textual numerical score for users who prefer

exact values. Moreover, horizontal bars are utilized to visually communicate confidence so that users can easily compare different recommendations.

By using these different types of indicators, users of the system are able to discern system confidence levels. This enables users to allocate the system's recommendations varying levels of trust and facilitate better decision making.

5.4 User Control Interface

Though most analytical processes are programmed to run without oversight, customers want to influence specific dimensions of the system's output to fit their needs. The problem was how to incorporate user-defined parameters to control the complexity of the system.

The control mechanisms, therefore, emphasize only a few core parameters that are most important to the system's functionality. These are things like risk appetite and duration of the analysis. All controls are described in non-technical, everyday English and companion notes detail what each control does. Figure 7 shows the user control panel that allows non-technical users to adjust a small set of high-impact parameters.

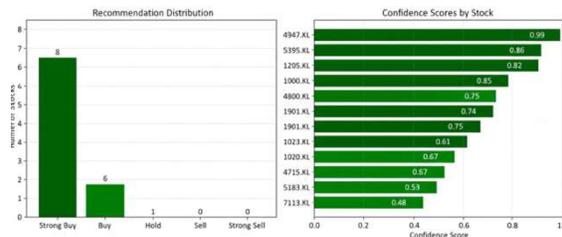


Figure 7: User control interface allowing non-technical users to adjust system parameters

The interface also immediately changes its visualizations and recommendations in response to control adjustments. This quick response helps users gauge the effects of their input and encourages them to interact more freely with the system to analyze their preferred market scenarios.

These different aspects have been carefully chosen to ensure the system's considerable capabilities are conveyed in a way that leaves users feeling confident and empowered rather than daunted.

6. INTERFACE EFFECTIVENESS EVALUATION

Evaluating the effectiveness of the AutoAgentic interface was needed to assess if the proposed design solutions enhanced the users'

ability to understand and utilize the AI-enabled insights. The evaluation considered the user's ability to assess how the interface provided and structured information, the level of communication efficiency, the ease of system interaction and the extent to which the provided explanations and controls facilitated informed decision-making. To address the evaluation questions, two financial dashboards that are widely used by investors were compared with the AutoAgentic interface.

6.1 Evaluation Framework

The assessment was focused on four parameters of user experience. The first was information clarity. A lot of financial dashboards have data that they throw at users, but users cannot figure out how to make sense of the information. Therefore, the assessment looked at how users can understand the system's summary of the current market conditions, recommendations and confidence level. The second aspect looked at the effectiveness of interaction. This consisted of how many steps or clicks users would need to accomplish critical tasks, such as viewing the market regime, portfolio recommendations, or answers to questions. A system that takes fewer steps, while still offering the same amount of detail, is likely to be more usable.

The third aspect looked at the explanation sufficiency. Users were asked to read the system's reasoning for each recommendation and judge whether the explanation was sufficiently clear, complete and relevant to their decision. The last aspect dealt with how accessible user controls were. This looked at whether users were able to easily find and modify important controls, whether they had control over settings and the level of control guidance they received to help them understand the impact of each control.

6.2 Comparison with Traditional Approaches

In trying to implement improvements, the AutoAgentic interface had to be compared to mainstream 'industry standard' financial dashboards. For each system, we measured performance using the four criteria established through the surveys. AutoAgentic performed better than the standard industry dashboards. Users were able to retrieve complex data more effectively and, in some cases, more quickly than through the conventional dashboards. For greater user efficiency, systems structured so that users can accomplish tasks in one click, as opposed to the multiple-click systems still prevalent in industry dashboards, are to be preferred. Users reasoned

explanations of complex data more positively than traditional dashboards. Table 1 compares the AutoAgentic interface with two traditional financial dashboards across multiple evaluation metrics to assess differences in functionality and user experience.

More often than not, traditional dashboards would provide users with a lack of contextual data and with only some of the technical indicators. In contrast, AutoAgentic offered users context with their reasoning so data was more easily digestible. Control interfaces were similarly rated higher for using conversational interface designs with the user and offering online help systems the user would use to reset through the automation. In all four diagnostic categories, the AutoAgentic interface scores were higher than the alternatives, overcoming the all too prevalent industry design limitations.

Table 1: Comparison of AutoAgentic and Traditional Financial Dashboards

Metric	AutoAgentic	Traditional Dashboard 1	Traditional Dashboard 2
Information Clarity	8.5/10	5.5/10	6.0/10
Interaction Efficiency	9.0/10	6.0/10	5.5/10
Explanation Adequacy	8.0/10	4.0/10	3.5/10
Control Accessibility	8.5/10	5.0/10	4.5/10

6.3 Key Findings

The evaluation provided several key insights. Users found appreciation for the lack of clutter in the interfaces for the system's market summaries/ Other commitments market summaries they explained. Users' grasp of current market scenarios and time efficiency improved due to the colour-coded regime indicators. Complementary charts and clear explanations of the most basic actions of the system illustrated a better interactive flow structure of the system. Users provided feedback on feeling less mentally bogged down and ability to quickly locate the data.

Equally as valuable as the aforementioned feedback was the use of plain language as a style of explanation. AutoAgentic builds greater user trust by replacing the jargon of traditional dashboards with conversational and warranted explanations. Ultimately, users were able to control and meaningfully adjust the system to avoid confusion.

Users showed better understanding owing to the descriptive nature of the labels and to the changes.

Overall, the evaluation worked as a publicity for the user-centred design, which was proved to have a great impact of trust and usability of the system. Users showed appreciation for the system and for the insights they were able to use, which were produced in the background by the system's AI models.

The importance of structured interpretation and clarity observed in this study is also consistent with prior research across diverse computational and decision-support domains. Studies on numerical modelling and mathematical approximation methods demonstrate that transparent formulation and systematic representation significantly improve users' confidence in complex computational outcomes [15-17]. Similar principles have been observed in medical decision-support and visual analytics systems, where intuitive visual interfaces and well-structured explanations enhance professional understanding and planning accuracy [18-19]. Beyond numerical and visual domains, research in affective computing and human-centred intelligence highlights that system interpretability plays a crucial role in user trust and emotional acceptance, as demonstrated in EEG-based emotion classification and sentiment analysis studies [20-22]. Furthermore, the integration of Kansei Engineering into chatbot-based assessment systems reinforces the idea that aligning system explanations with human emotions and cognitive expectations significantly improves interaction quality and perceived system reliability [23]. These findings collectively support the argument that user-centred interface design, explainability progressive information structuring are not domain-specific concerns, but rather foundational requirements for AI-driven systems intended to support informed human decision-making.

7. DESIGN PATTERNS

The process of designing the AutoAgentic interface resulted in several useful for fostering users' understanding, confidence and decision-making. These patterns are not only applicable to financial analytics, but also reveal design solutions usable in many other, more generalized AI systems. From the research, there are four design patterns. Each design pattern consists of practical ways of making the complex reasoning of the AI more interpretable and manageable to the users.

7.1 The Confidence Thermometer Pattern

Users frequently report that numerical confidence scores are hard to interpret independent of other informative materials. Users do not report knowing how to interpret a percentage score as high or low and they do not report knowing how that score impacts decision-making. The confidence thermometer reports confidence through a more interpretable and visual means. Figure 8 demonstrates the confidence visualization pattern, where colour-coded bars and graphical indicators are used to communicate the system's level of certainty.

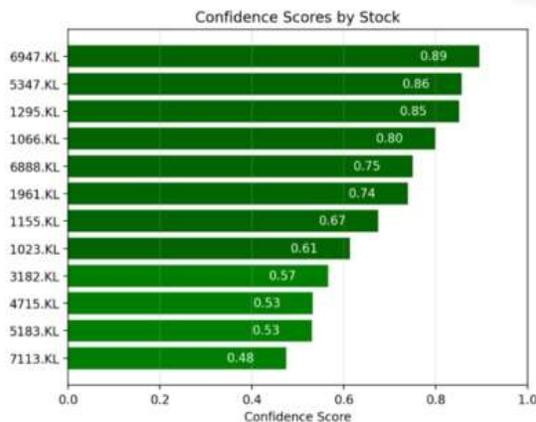


Figure 8: Confidence visualization pattern supporting user trust

The confidence thermometer uses a coloured bar that fills based on the confidence level the system has. The filled green region of the bar describes high confidence, the filled yellow region describes moderate confidence and the filled red region describes low confidence. In addition to the filled bar, a plain-language description of the confidence level is provided. Users also interpret the score better if they contextualize the displayed value compared to the confidence levels of other similar past predictions. This design allows users to gauge the level of confidence by working around the numerical scores and also by opening the filled bar, that they do not have to solely depend on the numerical score to gauge the level of confidence. The more visual system allows users to make decisions more prudently when they have high confidence as well as when the system works to signal low confidence and low levels of certainty.

7.2 Recommendation Pattern

Justifications increase adherence to recommendations. This strategy allows for the effective articulation of the relevant reasoning. To build this Why This Recommendation approach,

each recommendation should start with a succinct headline that summarizes the recommendation. This should be followed by a hierarchy of the system's determining influential factors, stated succinctly. Figure 9 illustrates how the recommendation explanation card integrates the decision outcome with its associated confidence level and key supporting factors.



Figure 9: Recommendation explanation card integrating decision outcome and supporting evidence

To be more informative, a nominal visual metric for determining high or low influential factors can be streamlined. This provides supporting evidence of the system's recommendation. To accommodate the interested user, the system can include a more technical description of the recommendation or model inputs and outputs. There, system's reasoning is articulated without cognitive overload without overwhelming the user of this system. It clarifies system recommendations to assist with the user's cognitive model of the overarching aim.

7.3 The Progressive Disclosure Pattern

AI models create an extensive amount of data which can quickly turn into visual chaos. Computer systems, however, do not display all the data at once. The Progressive Disclosure method tackles this problem by displaying data over time.

Users can focus on the main idea due to the initial details being presented outright, without the need to further interact with the computer. Deeper levels of information are hidden retractably in expandable boxes that the user can interact with at their own pace. Each of these levels is designed to keep the user oriented.

This approach is beneficial for different user levels. Novices can stay on the summary information, while experts can use the in-depth data anytime. This flexibility streamlines the interface and minimizes

the chance of users getting lost in the information and making the system overall less confusing.

7.4 The Plain Language Translator Pattern

Many artificial intelligence systems have incorporated jargon that pertains to certain industries but may not be common knowledge to the public. Doing so without context can create obstacles to comprehension. The Plain Language Translator pattern solves this dilemma by offering everyday explanations with technical jargon. Figure 10 shows how technical system concepts are translated into plain-language explanations supported by simple visual cues. This approach reduces reliance on specialised terminology and helps non-expert users form accurate mental models of the system's reasoning.



Figure 10: Plain language translation pattern for communicating technical concepts to non-expert users

For example, the system can introduce an idea that is technical in nature and display an example that is comparatively simple and practical. The idea can even be visualized in an illustration. In the event that users are interested in the technical definition, they can be provided with an optional advanced section. Also, an entire glossary may be dedicated to common terms of a given domain. This pattern is intended to circumvent the barrier of specialized vocabulary that prevents users from comprehending the system. Additionally, it fosters the accumulation of familiarity with technical concepts.

8. DISCUSSION

8.1 Implications for AI System Design

This study illuminates the possible implications of designing AI systems for predictive analytics in real-world scenarios. The first and most pivotal revelation is that transparency is necessary for the system's acceptance. If users understand the rationale that guides the system, they will be more likely to accept the suggestion and act upon it. [4] also made such observations, which, in the context of finances, become highly relevant as users are more unsure of the criteria that drive the fluctuations of the market. The other implication pertains to information simplicity. The study showed that users perceived

complicated market trends more easily when they were presented with clearly articulated and structured information. This is in line with [7], who posited that information that is presented in a clear and structured format is more likely to be understood. The system also improves the users' experience by controlling the amount of information that is presented at a time. When information is presented in layers, the system can lower the cognitive load and encourage users to delve in depth at their own time.

The study also emphasized the importance of user choice. Even when systems are fully automated, users prefer to delimit the range in which the system will operate. This allows users to bring the system in line with their own preferences and risk assumptions [2]. Research done by [5] shows how even users' minor technical actions enhance trust-building. Users of the AutoAgentic System get the opportunity to keep the system's technical complexity hidden, as complexity is one of the main technical barriers of user-system interaction.

Another related observation is technical jargon. Users have little or no familiarity with the technical terminology of financial review or machine learning. Simplifying jargon into layman's is a huge benefit, as users are empowered to positively engage with the system. This is consistent with [14] who reported a greater likelihood of users attaining a correct mental model of an AI system when the model was explained in simple terms. All these implications indicate that the performance of an AI system is linked to the sophistication of the AI's predictive abilities and the ease of loss of that information to the user. Predictive abilities are unlikely to be the primary underlying cause of a user's loss of information. Predictive abilities, along with clarity, intentional visual design, structured indicators of confidence and control of actions, create a user loss of information and should be one of the primary focuses of the AI system to build user trust.

8.2 Limitation and Future Work

While this study provides valuable insights, several limitations should be acknowledged:

(1) Sample Size and Representativeness.

The comparative evaluation involved 45 participants recruited primarily from Malaysia. While adequate for detecting medium-to-large effect sizes (Cohen's $d > 0.6$, power = 0.80), this limits generalizability across broader demographic and cultural contexts. Malaysian investors may exhibit specific risk preferences and technology adoption behaviors differing from other populations. Future research should conduct multi-country studies examining how cultural differences in trust, risk

perception and communication preferences influence design pattern effectiveness. Larger-scale studies with diverse socioeconomic backgrounds would strengthen external validity.

(2) Limited Duration of Evaluation.

Our study captured user experience during a single 90-minute session. This short-term evaluation cannot assess how sustained usage over weeks or months affects trust development, learning curves, or habituation effects. Long-term field studies are needed to examine whether initial positive impressions persist, how users' mental models evolve with repeated interaction and whether design patterns remain effective as users gain expertise. Longitudinal research could reveal whether certain patterns (e.g., Progressive Disclosure) become less necessary for experienced users, informing adaptive interface designs.

(3) Domain Specificity.

Although we argue design patterns are domain-agnostic in principle, empirical validation was conducted exclusively within financial decision support. Medical diagnosis, legal analysis, environmental monitoring and other high-stakes domains involve distinct types of uncertainty, risk, specialized vocabularies and regulatory constraints requiring pattern adaptation. For instance, medical explanations may need different confidence visualization due to life-or-death consequences, while legal applications may demand exhaustive audit trails. Systematic cross-domain validation studies are essential to establish generalizability and identify necessary contextual adaptations.

(4) Selection of Comparison Systems.

Our evaluation compared AutoAgentic against two established financial dashboards not specifically designed with explainability as primary goal, potentially inflating measured advantages. Future studies should include comparisons with other XAI-enhanced financial tools or prototype systems implementing alternative explanation approaches (counterfactual explanations, example-based reasoning) to precisely isolate contributions of specific design patterns versus general XAI implementation.

(5) Participant Expertise Distribution.

Our sample was skewed toward intermediate users with bachelor's degrees or higher. Professional financial advisors and algorithmic traders were excluded, limiting insights into expert user perceptions. Additionally, individuals with very low digital literacy were underrepresented. Future research should examine how design patterns perform at expertise extremes, specifically whether complete novices benefit more from certain patterns

while experts perceive them as redundant. Understanding these boundary conditions would inform adaptive interface strategies.

(6) Measurement of Trust and Decision Quality.

Our evaluation relied primarily on self-reported perceptions rather than objective measures of decision quality (actual investment returns, calibration of confidence judgments against outcomes). While subjective trust predicts system adoption, future research should incorporate behavioral measures such as alignment between user decisions and system recommendations under varying confidence levels, calibration accuracy and long-term investment performance to validate whether improved interface design translates to better decision outcomes.

(7) Cultural and Linguistic Considerations.

Although conducted in Malaysia with diverse participants, all interfaces and materials were in English. Language proficiency may have influenced comprehension of plain-language explanations. Cultural factors influencing interpretation of visual metaphors (thermometer for confidence), color associations (red/yellow/green for risk) and preferences for direct versus indirect communication were not systematically examined. Cross-cultural research comparing pattern effectiveness across linguistic and cultural contexts would enhance understanding of universal versus culture-specific design requirements.

8.3 Broader Applications

The findings on the design patterns in the study do not extend only to analytics in finance. In the health sector, patients are likely to benefit from recommendations on treatments and an explanation of the associated risks. In the legal field, summaries of documents, intended to be automated, can provide non-attorney users access and understanding plain language. Visual approaches to climate change or pollution risk monitoring used in educational systems offer a way to assist communities in understanding personalized the learning suggestions. Enhanced learning recommendations utilize device structure to justify the pathway of the educational path suggested to be followed.

The applications described above do indicate that user-centred design is not a concern of a specific field and poses as a fundamental necessity of any AI system intended to assist human decision making. Clarity, transparency, progressive disclosure and meaningful control are features design AI systems to improve understanding and trust from users. These would be applicable to a cross-section of tools that rely on AI.

9. CONCLUSION

The purpose of this study was to understand how thoughtful interface design could be used to improve users' understanding of and engagement with AI-driven decision-support systems. Using AutoAgentic as an example, the study attempted to demonstrate how the ability to analyze information could be significantly more beneficial to users if the analytical results could be presented in a clear, accessible and trustworthy manner. The design strategies employed in this research, including the visualization of market regimes in simple and meaningful ways, the provision of structured explanations, intuitive indicators of confidence and the meaningful empowerment of users, demonstrate how transparency and clarity improve user experience.

The identification of four design patterns resulting from iterative design as a primary contribution of this work is recognized. The patterns of the Confidence Thermometer, Why This Recommendation, Progressive Disclosure and the Plain Language Translator capture domain-independent actionable practices that can be employed in diverse AI systems. These patterns advocate the principle of transparency in automated reasoning and can guide the development of resources that complement human decision-making. The findings support a more general claim that the effectiveness of an AI system is a function of the system's ability to communicate the results is as important as the quality of the system's algorithms. AI-backed recommendations which include well-articulated reasoning and explanations, as well as simple and straightforward graphics and controls are perceived, adopted and used more than those which do not. As AI advances, the interfaces to be used must centre on the human ability to understand these systems.

This paper adds to the discourse on human-centred AI by illustrating the level of interface design needed to reconcile advanced computational capabilities and the design to facilitate a human's mundane decision-making process. When the design process centres around the users, systems AI systems become more efficient, more transparent and much more useful as they centre around the information in the way users intuitively want to understand.

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