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Interactive visual study for residential energy consumption data

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ABSTRACT

Interactive data visualization tools for residential energy data are instrumental indicators for analyzing end user behavior. These visualizations can be used as continuous home feedback systems and can be accessed from mobile devices using touch-based applications. Visualizations have to be carefully selected in order for them to partake in the behavioral transformation that end users are encouraged to adopt. In this paper, six energy data visualizations are evaluated in a randomized controlled trial fashion to determine the optimal data visualization tool. Conventional visualizations, namely bar, line, and stacked area, are compared against enhanced charts, namely spiral, heatmap, and stacked bar, in terms of effectiveness, aesthetic, understandability, and three analysis questions. The study is conducted through a questionnaire in a mobile application. The application, created through React Native, is circulated to participants in multiple countries, collecting 133 responses. From the received responses, conventional plots scored higher understandability (by 22.74%), effectiveness (by 13.44%), and aesthetic (by 10.54%) when compared with the enhanced visualizations. On the flipside, enhanced plots generated higher correct analysis questions' responses by 8% compared to the conventional counterparts. From the 133 collected responses, and after applying the unpaired t-test, conventional energy data visualization plots are considered superior in terms of understandability, effectiveness, and aesthetic.

1. Introduction

In modern society, excessive domestic energy consumption is an issue surpassing all other dilemmas despite the increasing awareness of existing environmental problems (Ouyang and Hokao, 2009). For instance, global heating and cooling energy consumption is expected to grow by 84% by 2030, according to Ürge-Vorsatz et al. (2015). Paz et al. (2012) emphasizes that it is of the utmost importance that future leaders, scientists, and engineers be more aware about the current and future problems related to environmental sustainability. Consequently, recent research has focused on controlling household energy usage for better efficiency in energy consumption either by studying the acceptability of energy-saving measures with different physical characteristics as in Poortinga et al. (2003), increasing the energy consumption understanding by initiating a large-scale energy monitoring campaign as Almeida et al. (2011) did, or analyzing the residential power consumption trends in the world in a certain period of time as the work of Pablo-Romero et al. (2017).

Energy consumption is mainly affected by several key factors related to the end user's habits, age, gender, income level, household structure, and educational background, as mentioned by Yue et al. (2013). According to Huebner et al. (2013), behavioral change to new habits is opposed by the repetition of a certain behavior in a usual pattern. It is evident that state-of-the-art techniques, strategies, and models can change inefficient energy usage habits to efficient ones. The trans-theoretical model (He et al., 2010), the reasoned action approach (Fishbein et al., 2011), the motivational interviewing (Miller and Rollnick, 2012), and the reinforcement learning (Hu and Zira, 2014; Decker et al., 2016) are some examples of such techniques and strategies. However, in this context, the adoption of modern technology is lightly addressed. On one hand, smart home energy moderating systems exploiting energy data visualization and wireless power metering are proposed by Jahn et al. (2010). On the other hand, tolerating heating and cooling settings is achieved in the case study Nest Thermostat (Nest, 2018), based on advanced algorithms employed for the understanding and prediction of end users' behavioral patterns.

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Although the aforementioned state-of-the-art studies present energy profiles, behavioral change towards efficient energy behavior is not applied. For this purpose, combining behavior change models, informative data visualization, and personalized recommender systems is of utmost significance to be deployed in practical systems.

Data visualization systems have been a key part of many research and development fields. For instance, they are used to aid clinicians in making correct diagnostic imaging orders (Rayo et al., 2015), to visually explore differential gene expression data (Simon et al., 2017), and to organize and reduce narrative data into a single geographical plot (Irwin et al., 2017). Moreover, they are used in visualizing complex communication network (Verspoor et al., 2018), in comparing carbon footprint locally (Engel et al., 2012), in relating different films using minimum spanning dendrograms (Vlachos and Svonava, 2013), and automatically visualizing big data (Golfarelli and Rizzi, 2020). The variety of applications that this tool impacts are tremendous and important. From that perspective, it is essential that such tool is also utilized in the energy sector, especially the residential branch, to educate consumers and buildings' owners about their buildings' consumption. This in turn helps users monitor and control their energy usage, since people are normally unaware of their energy consumption, simply because they do not see it, as mentioned by Trinh and Jamieson (2014). Visualizing the total energy consumption of a household, the financial impact it has, and the main appliances causing it, whether it is efficient or not, can significantly influence consumers. This influence is either in terms of performing the necessary reductions in energy consumption, or simply maintaining the same consumption if it is deemed efficient. Also, the feedback, in form of bills or warnings (in case of excessive consumption), from utilities is naturally infrequent, preventing such feedback from having significant impact. These visualization systems can be used as continuous home feedback systems and can be accessed from mobile phones and tablets.

In this paper, the efficacy of six energy data visualizations is evaluated in a randomized controlled trial fashion to determine the favored energy data visualizations. Real energy data from the Individual Household Electric Power Consumption Data Set (IHEPCDS) (Hebrail and Berard, 2012) are visualized in the proposed mobile application in an aggregated form on multiple levels. To summarize, the main contribution axes of the paper are as follows:

- To the best of the authors' knowledge, this is the first study that uses a novel interactive mobile application survey, built from scratch using React Native, to display energy visualizations and acquire participants' responses
- The survey is conducted via the mobile application to measure the suitability of conventional and enhanced visualization plots for improving energy saving in buildings. We conducted the study in this manner to catch the user experience for these plots on the final destination, which is a mobile application.
- A set of enhanced smart energy usage visualizations are created/introduced, including heatmap chart, stacked bar chart, and spiral chart, which provide more options to present energy consumption data than the conventional visualizations.

The outcome of this study are utilized in a greater umbrella framework, namely "consumer Engagement towards Energy saving behavior by means of Exploiting Micro Moments and Mobile recommendation systems", abbreviated as $(EM)^3$ (Bensaali et al., 2020). It is a research initiative that aims to endorse domestic energy-saving behavior with the use of a recommender system, powered by artificial intelligence algorithms and data visualizations (Alsalemi et al., 2020). It includes four main components: (1) Data collection (i.e. consumption footprints and ambient conditions) at the appliance level (Alsalemi et al., 2019); (2) Classification and anomaly detection using micro-moments to analyze consumers' behavior and points of potential improvement (Alsalemi et al., 2019); (3) Generating personalized recommendations to achieve those points of potential improvement (Sardianos et al., 2019); and

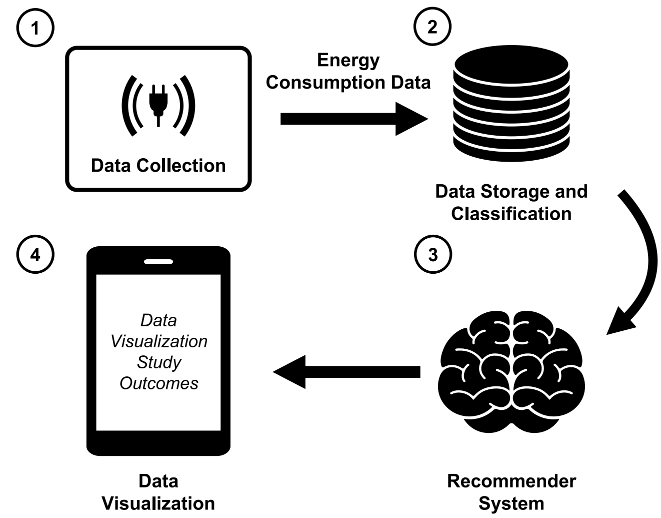

Fig. 1. Overview of the $(EM)^3$ framework.

(4) Data visualization where energy consumption data are portrayed in a highly engaging and effective manner. Data visualization tools can be used for multiple purposes that include a representation of historical energy consumption data, along with being an assistive tool for recommender systems to explain the suggested recommendations for end users. Fig. 1 shows an overview of the framework. The so called "best" data visualization charts investigated in this study will be used later in the framework's deployment.

For the data collection module, it is the basis for collecting necessary data that aids the system in understanding the users' consumption preferences under certain environmental conditions within the household, linking it to the external weather conditions. To that end, it collects data related to energy consumption at the appliance level, ambient temperature, humidity, luminosity, temperature, and consumer's occupancy. The second module is tackling dataset storage, management, and classification of the collected data. It aims to create an energy profile of a consumer where it can be utilized to determine the energy consumption pattern for that consumer in a certain household. Moreover, it helps in detecting anomalous energy consumption patterns, such as having the air conditioner turned on while the weather is very cold within the house, or having the lights turned on in a room, when no one is within the vicinity of that room. Thus, it classifies what is considered as an anomalous consumption and what is not. Thirdly, the recommender system tries to suggest certain actions that puts the interest of the consumer as a first priority. Recommender systems have been used extensively in e-commerce and content streaming platforms, where they would "recommend" certain products/series to buy/watch based on the user's current choices. The same can be applied in the energy context, where a recommender system can take advantage of the consumers' available information so that it can recommend certain actions, which will further optimize their consumption, considering their preferences along the way. Moreover, it can incentive recommendations that it provides by highlighting the effects they will produce when the recommended suggestions are accepted and acted upon. Finally, the data visualization module is as important as any of the previous modules. The idea is to utilize such graphs to present collected data in an aesthetic, easy-to-understand graphs that can raise the consumers' awareness regarding their consumption. Moreover, it can show consumers their anomalous consumption easily on a graph, and visually describe the impact that the recommendations will have on if they are accepted.

The remainder of this paper is organized as follows. Section 2 summarizes recent work in energy data visualizations. Section 3 discusses the study methodology. Section 4 presents the obtained sample size and the employed enhanced and conventional data visualizations. The results are reported and discussed in Section 5. The paper is concluded in Section 6.

2. Related work

Smart grids idea is about collecting data using Internet of things (IoT) sensors at multiple levels in the supply chain, from the electric utility until the end user. Consequently, better and efficient management of assets and services can be achieved. According to Leroy and Yannou (2018), consumers have become unpredictable more than ever in their consumption, thus, smart systems, aided by the IoT sensors, can reduce this uncertainty, which in turn will help utilities in consumption estimation and resources' allocation. Not only that, but energy consumption visualization is easily integrated into the idea of smart grids/cities due to the abundance of collected data. Data mining techniques in the energy field play a huge role in understanding the massive data that is being collected (Li et al., 2020), where information about individuals' power consumption can then be extracted and visualized (Wilcox et al., 2019).

2.1. Energy consumption visualizations

With data visualization, consumers can acquire a better understanding of their appliances' consumption, showing how they contribute to the whole energy consumption. Thus, with the right incentive, consumers can become more aware and more energy-efficient. For instance, some studies have already shown interest in energy consumption visualization inside buildings (Smith et al., 2019; Chen et al., 2020), where the former is interested in light commercial buildings' energy consumption visualization, and the latter is focused on domestic consumption visualization and human behavior simulation. In addition, augmented reality (AR) is also utilized to enhance the consumers' awareness regarding electronic devices/appliances consumption (Bekaroo et al., 2018).

From the reviewed studies like Bonino et al. (2012), such visualization charts can help the users from different aspects including:

1. To identify consumption trends which will enable them to reduce the consumption. For example, the trends might show that the consumption is at its highest in the evening between 4–5 PM, when the user's family is back from work/school.
2. To determine the energy consumed by individual appliances so that the users can identify which appliances are responsible for high energy consumption.
3. To investigate the impact of the consumption either monetarily or environmentally. For example, the visualization might indicate the cost of operating a washing machine or the number of trees that need to be planted to compensate the consumption.
4. To keep track of the energy consumed by individual members of a household, so that members with high consumption can be made aware of their consumption while informing them with more intelligent choices.
5. To be able to set a goal for everyday consumption and receive tips on how this goal can be achieved by making intelligent choices like switching off an appliance.
6. To enable the control of appliances from the visualization directly. For example, if the visualization notifies that an appliance is consuming high energy, then the user should be able to switch off that appliance.

Using data visualization charts to show users their energy consumption can have positive effects in reducing it, as visualizations are capable of tackling the most important factor in the electricity supply chain; the human factor. With the rapid increase and growth of technologies, mobile phones have become an integral part of people's lives and are used for a variety of applications. Weiss et al. (2010) confirmed the suitability of using mobile devices to track energy consumption. They have also found that mobile phones are suitable for the task due to the high interactivity and portability they offer. While, Micheel et al. (2015) found that users prefer a mobile device to keep track of their water and energy consumption due to its quick access and instant alerts. Hence, our visualizations are built to be used on a mobile application. According to Blumenstein et al. (2016), through their increasingly widespread usage, mobile devices have become a highly important target environment for Visualization of Knowledge. However, much too little focus has been given to the assessment of digital simulation strategies on mobile devices.

In an effort to understand the commonly used visualizations, we reviewed the papers that visualized energy consumption in a single unit, in multiple units, and over wider geographical areas. Though we are only interested in visualizing the energy consumption in a single unit, we reviewed related work that visualized consumption over multiple units and wider geographical areas as the fundamental visualization remained consistent across all categories. These visualizations often visualized the consumption for a single unit and then built an extra layer of visualization on top of the fundamental visualization to aggregate the consumption across several units.

We also decided to review only 2D visualizations as they are better suited for users who are not very skilled with computers (Sebrechts et al., 1999). With the evolution of mobile phones, users often turn to mobile applications for entertainment, technology, home-automation, gaming, etc. Hence, we decided to create a mobile application that monitors energy consumption that would be useful for energy consuming end users.

The energy visualizations are reviewed and classified based on categories loosely inspired from the authors of Bonino et al. (2012) and Murugesan et al. (2015). These categories will help the readers identify popular features supported by the visualization, the target platform they are used in, the area for which consumption is visualized, and other details that describe the visualization.

1. **Central Theme: *Direct Feedback, Historical Trends, or Goal-Setting?*** While there are many visualizations available for visualizing energy consumption, the common theme of the visualizations can be categorized under three main categories which are descriptive of the main tasks supported by these visualization. The developed visualizations often adopt one or more central themes and can be broadly classified as:
   (a) **Direct Feedback + Tips (DF+T) Visualization**: These visualizations provide feedback to the users about which device or where (e.g. in which room) they are consuming more energy, and provides tips on how they can cut down on their consumption. Some of the tips may include switching off an appliance that is consuming significant amount of power to balance the electricity load.
   (b) **Historical Trends (HT) Visualization**: These visualizations show the trends in consumption to the user. For example, from these trends, users might be able to recognize that the highest consumption is during weekends so they can take actions to lower the consumption during those periods.
   (c) **Goal-Setting (GS) Visualization**: These visualizations help the users to set an energy consumption goal that can help them to be rewarded if they abide by the set goal. These rewards are often monetary in nature and help motivate the users in achieving their targets. This feature can be considered as a bonus add-on feature that is often coupled with one or both of the other two categories who are more essential in nature.

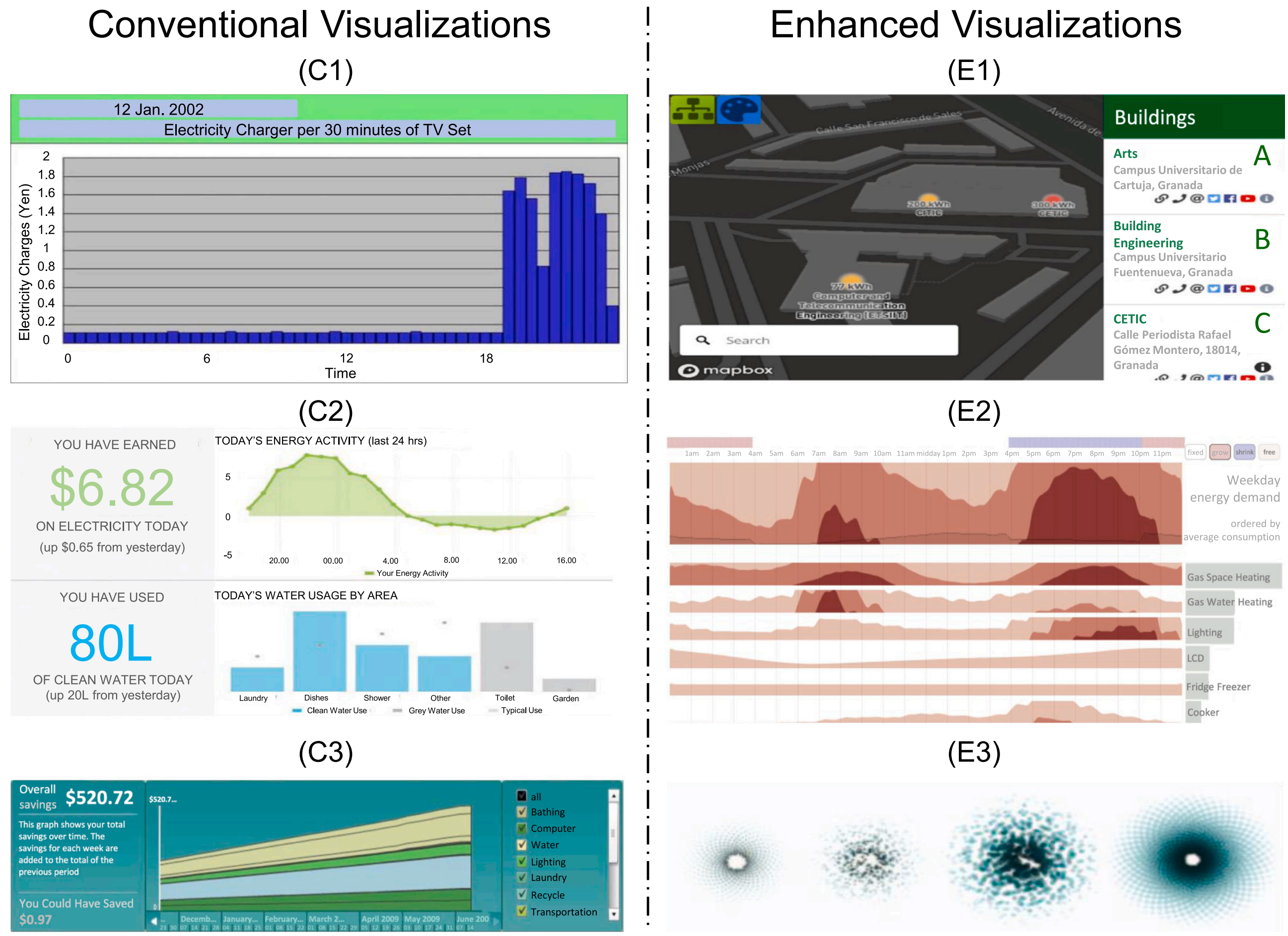

Fig. 2. Examples of conventional and enhanced visualizations: (C1): ECOIS [Bar chart] (Ueno et al., 2006), (C2): ALIS Dashboard [Line chart, Bar chart] (Bartram et al., 2010), (C3): StepGreen.org [Stacked area chart] (Grevet et al., 2010), (E1): VIMOEN [Map] (Ruiz et al., 2020), (E2): Demand Horizon [Horizon chart] (Goodwin et al., 2013), and (E3): Phyllotaxis [Phyllotaxis] (Rodgers and Bartram, 2011).

In addition to the "Direct Feedback" that is provided by the Residential Stock Viz. proposed by Mattinen et al. (2014) and the Power and Energy Viz. discussed in Monigatti et al. (2010) visualizations, they also allow users to analyze the impact of their decisions such as the impact of switching off lights. Energy Control System (ECoS) (Murugesan et al., 2017) takes it a step further by offering tips to combat the consumption while providing the ability to control the appliances from the visualization.

2. **Type of Visualization: *Conventional or Enhanced?*** Most of the energy visualizations are built using conventional charts such as pie charts, bar charts, line charts, area charts, to name a few. These charts are mostly static, offer little to no interaction, and often visualize the default hourly consumption. On the other hand, enhanced visualization charts offer better interactivity and more in-depth detail about the consumption such as appliance-level consumption, per-minute consumption, etc. We use the term "Enhanced visualizations" to include novel representations, visualizations that are considered an enhanced version of conventional ones, and pre-existing visualizations that have not been explored for visualizing energy consumption. For example, advanced versions of conventional visualizations like time-pie charts, stacked-bar charts, time-area charts, which are advanced versions of the conventional pie, bar, and area charts are classified as enhanced visualizations as they offer more detail and interactivity than the their conventional counterparts. Other enhanced energy consumption visualizations include coloring the layout of the house/building or map of the country/world, heatmaps, and artistic visualizations like Phyllotaxis, Hive and Pinwheel visualizations. Some examples of conventional and enhanced visualizations are shown in Fig. 2.
3. **Geographical Area that the Visualization covers: *Single Unit or Multiple Units?*** The visualizations can visualize the consumption of a single unit as in the case of a user's house, multiple offices in the case of a building, or can cover larger geographical areas to monitor the consumption of different cities/states in a country. Charts that visualize the energy consumption of a single unit are mostly used by residents to visualize their own energy consumption. On the other hand, multi-units charts are mostly used by energy managers to monitor the consumption of an entire building. This gives an indication of which apartments/offices are consuming the most energy in a building, or which buildings are consuming the most energy if the energy manager is responsible for a group of buildings. This feature is also occasionally used by residents to compare their consumption with other residents. The multi-units visualizations can also be extended to wider geographical areas like countries to monitor the consumption of individual states or districts. The Adaptive Living Interface System (ALIS) Dashboard portrayed in Bartram et al. (2010) is an interesting tool capable of visualizing the consumption of a single house, while giving the users the ability to compare their consumption against other houses in a community.
4. **Primary Feature of the Visualization: *Time or House/Building Layout?*** Many visualizations often monitor consumption over a

period of time, while some visualizations monitor the consumption over different rooms in a house, different apartments in a building, or over wider geographical areas. The visualizations that monitor consumption over time provide a general indication of the hourly consumption. To a certain extent, it can also shed some light about the consumption of the different appliances if a user can track his/her activities in a day. For example, it can help users in remembering their usage of the washing machine between 10–10:30 AM. On the other hand, energy consumption visualization using an apartment/building layout provides more details about the critical areas with high consumption. It allows users within a household to implicitly know what appliance or individual generated that consumption based on their knowledge of the family members whereabouts.

From Table 1, it is clear that most visualizations are developed to be used as a web application, with very little work focused on mobile applications. Hence, our visualizations are developed to visualize and track energy consumption from a mobile interface. The table also indicates that the popular form of visualizations are line and bar charts with very few studies using stacked bar charts and heatmap visualizations. Our mobile application uses two types of visualizations, namely enhanced and conventional, to visualize the energy consumption. Each type is associated with three types of visualizations. On one hand, the ones belonging to the conventional visualizations group include:

1. **Bar chart** to visualize the monthly consumption of a house.
2. **Line chart** to visualize the monthly consumption of a house as a continuous line.
3. **Stacked Area chart** to visualize hourly appliance-level consumption as stacked areas.

On the other hand, the three charts belonging to the enhanced visualizations group include:

1. **Heatmap** to visualize the consumption in intervals of 10 min with added interactivity to show the consumption per room when a cell in the heatmap is clicked.
2. **Stacked Bar chart** to visualize the appliance-level consumption per hour. The chart allows the user to select the appliances from a scrollable list.
3. **Spiral chart** to depict a concise representation of the consumption over a year which allows users to easily detect trends over months and seasons. To the best of our knowledge we are the first to use a Spiral Chart to track energy consumption over a period of a year.

Hence, we predominantly developed linear visualizations with the exception of the spiral chart. In accordance with Cleveland and McGill's finding, we used visualizations for which all the elements in the charts are positioned along a common axis, the width of the bars in the bar chart and the area of the elements in the heatmap visualizations are also kept at a constant size for easier perception. The heatmap also uses a gradient coloring to visualize the level of consumption. The spiral chart which uses polar coordinates is used as it compactly visualizes the consumption over a period of a year, as opposed to using a linear chart using a cartesian representation that would require more screen space which cannot be afforded on the small mobile screen display.

2.2. Experiment studies

Some experiment studies have been conducted to assess to what extent visualizations can impact the energy consumption in residential buildings. This is the case of Herrmann et al. (2017), where they conduct an experiment study to assess whether end users comprehend domestic energy feedback. Specifically, 43 participants have been involved, and their knowledge has been assessed to evaluate achieved behavioral change after being trained with various kinds of energy consumption data visualizations. The participants have been invited to play an energy game both before and after being trained with data visualizations. Moving forward, because it is not straight forward to satisfy all the users using static ready-made visualization plots when developing an energy efficiency system, Watanabe et al. (2013) conduct a questionnaire study to collect the users' requirements in terms of energy data visualization. The questionnaire has been conducted using a web application to help in selecting convenient visualization graphs from the questionnaire's answers. In a similar approach, Costanza et al. (2012) has evaluated the impact of using an enhanced interactive visualization, namely FigureEnergy, to comprehend when, how, and, to what end, each specific energy usage has been performed. Explicitly, 12 participants (out of the original 15) have been involved in this study through installing sub-meters in their households and running the FigureEnergy application for a two weeks period.

The premise of this paper is to develop a mobile application that can be used by the general public to monitor and conserve energy. 2D visualizations are used since they are easier to explore, develop, and employ when compared with the 3D ones on smaller displays. Hence, the decision is to develop the application using 2D techniques, while the review of 3D visualizations is considered to be outside the scope of the review of this paper. Some of the popular 2D energy visualization applications have been summarized in Table 1.

3. Methods

In this section, the proposed methodology to obtain the achieved results is presented. Firstly, the randomized controlled trial scheme that has been deployed to conduct the study is discussed, along with the questions that are given to the participants to be answered. Secondly, the working scheme behind the React Native application is discussed, where the GitHub repository for the application is publicly shared to be utilized, especially if others decided to deploy and build over the graphs that are utilized in our study.

3.1. Randomized controlled trial

The study design is illustrated in Fig. 3. The study follows a randomized controlled trial design, which splits the participants into two groups: the control group that evaluates the conventional visualizations, and the intervention group that evaluates the enhanced visualizations.

The assessment can be summarized as follows:

1. Recruit study sample (via emails, social media channels, and over the $(EM)^3$ project's website Bensaali et al., 2020).
2. Randomize sample and send application link to each participant (participants did not have the application installed before commencing the study). This is done through a random group assignment accomplished within the mobile application.
3. Participants run the application and rate each of their respective group's visualizations based on the aforementioned criteria (i.e. effectiveness, aesthetic, and understandability), along providing answers regarding the three analysis questions.
4. Following data collection, responses are analyzed per group, where a comparison is conducted at the end to decide whether to reject (or fail to reject) the study hypothesis.

For this randomized controlled trial, the null hypothesis is defined as the following: the two groups, assessed using the application questionnaire, show no statistically significant difference in favoring a group over the other. This is tested using three variables simultaneously namely, understandability, effectiveness, and aesthetic. To analyze the participants' feedback, responses are averaged, grouped by category (i.e. enhanced or conventional), and compared accordingly. The complete list of questions used in this study can be found on our website (Bensaali et al., 2020). The complete list of questions used in this study are attached as supplementary material. Below are the main qualitative questions asked for each provided visualization:

Table 1
Comparison of popular energy consumption visualizations.

Name of the Viz.	Target Platform	Central Theme	Type[a]	Primary Feature[b]	Primary Viz.	Covered Area
House-layout prototype (Bonino et al., 2012)	–	DF & GS	E	L	Coloring	Single unit
Energy research Centre of the Netherlands (ECN) Viz. (Van Wijk and Van Selow, 1999)	–	DF & HT	E	T	Calendar + Line	Multi-units
Residential Stock Viz. (Mattinen et al., 2014)	–	DF	E	L	Map	Multi-units
Power and Energy Viz. (Monigatti et al., 2010)	–	DF	E	T & L	Radar + Pie + Layout	Single unit
Energy Control System (ECoS) (Murugesan et al., 2017)	Web	DF+T	E	L	Map + Line + Pie	Single unit
Energy Consumption Information System (ECOIS) (Ueno et al., 2006)	–	DF+T & HT	C	T	Bar + Pie	Single unit
Adaptive Living Interface System (ALIS) Dashboard (Bartram et al., 2010)	–	DF+T & HT & GS	C	T	Line + Bar	Community
StepGreen.org (Grevet et al., 2010)	Web	DF & HT & GS	C	T	Bar + Pie + Line	Community
VIsual MOnitoring of ENergy (VIMOEN) (Ruiz et al., 2020)	Web	DF & HT	E	L	Map + Pie + Line + Area	Multi-units
Artistic Viz. (Rodgers and Bartram, 2011)	–	DF	E	T	Phyllotaxis + Pinwheel + Hive + Line + Stacked-bar	Single unit
Demand Horizon Viz. (Goodwin et al., 2013)	Web	DF+T & HT	E	T	Horizon charts	Multi-units
Consumption Signatures Viz. (Goodwin et al., 2013)	Web	DF+T & HT	E	T	Heatmap	Multi-units
SmartHome Heatlines Viz. (Goodwin et al., 2013)	Web	DF & HT	C	T	Line	Multi-units
Ownership Groups Viz. (Goodwin et al., 2013)	Web	DF & HT	C	T	Bar + Box	Multi-units
Figure Energy (Costanza et al., 2012)	–	DF & GS	C	T	Line	Single unit
Time-pie Viz. (Masoodian et al., 2013)	–	DF & HT	E	T	Time-pie	Multi-units
Time-stack + Time-pie Viz. (Masoodian et al., 2015)	Mobile	DF & HT	E	T	Time-stack + Time-pie	Multi-units
Electric-Save (E-SAVE) (Soni and Lee, 2012)	Mobile	DF+T	E	L	Layout + Radar + Pie	Single unit
Energy-Efficient Home (E^2 Home) (Ghidini and Das, 2012)	Web	DF+T & HT	C	T	Line + Linked map	Single unit
Google + Microsoft Power Meter (Ghidini and Das, 2012)	Web	DF & HT	E	T	Horizon charts	Multi-units
Sensor-Actuator Gateway Agent (SAGA) Dashboard (Buevich et al., 2011)	Mobile	DF & HT	C	T	Bar + Pie + Line	Multi-units
WattDepot Visualizer Client for Smart Grids (Brewer and Johnson, 2010)	–	DF	C	T	Line	Country
Real-time price Viz. (Nilsson et al., 2017)	–	DF	C	T	Stacked-bar + Line	Multi-units
energy Visualization (eViz) for carbon reduction(Pahl et al., 2016)	–	DF	E	L	Thermal imaging	Single unit
Power Consumption Viz. (Ali and Kim, 2013)	Web	DF & HT	E	L	Layout + Line	Multi-units
VISUAL-TimePAcTS software (Ellegård and Palm, 2011)	–	DF	C	T	Grids + Stacked-bar	Single unit
Handy Feedback (Weiss et al., 2009)	Mobile	DF & HT	C	T	Gauge + Bar + Line	Single unit

[a]C: Conventional; E: Enhanced.
[b]T: Time; L: Layout.

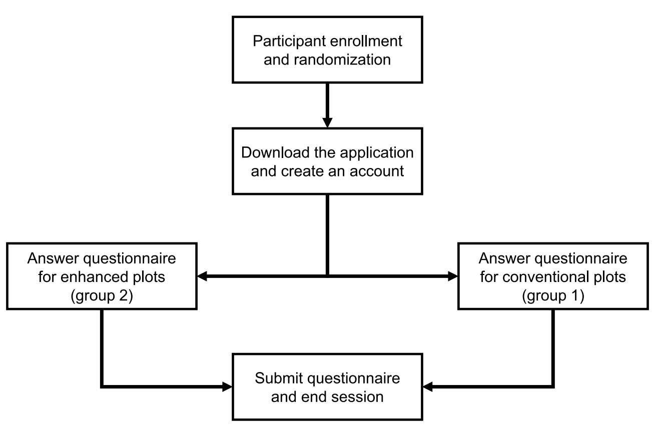

Fig. 3. Study's design scheme.

1. How effective is the provided visualization in portraying power consumption information? *(1 not effective at all – 5 very effective)*
2. How easy to understand is the provided visualization in portraying power consumption information? *(1 not easy at all – 5 very easy)*
3. How visually pleasing is the provided visualization? (*1 not visually pleasing at all - 5 very visually pleasing)*
4. In terms of quantity, how do you describe the amount of data presented? *(options: a. sparse (not enough), b. adequate (enough), c. excessive (very complex))*

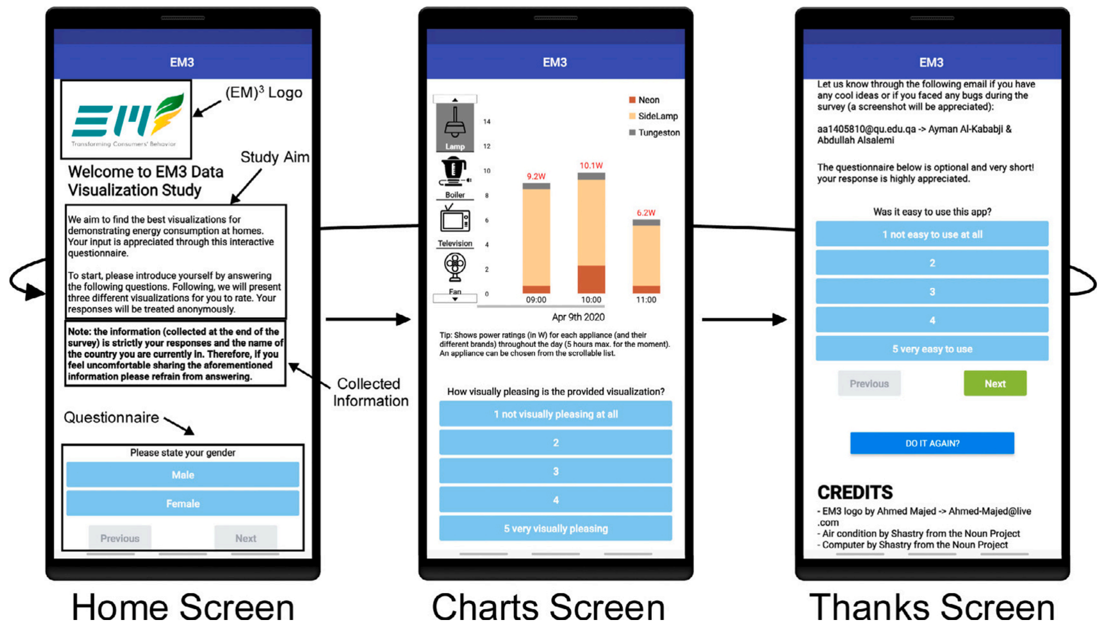

Fig. 4. Application usage cycle on a smartphone.

It is noteworthy to mention that each visualization is designed to portray energy data in a different way and may present insight to end users. Therefore, visualizations presented in this study may not present the same energy consumption data due to their design differences.

3.2. Questionnaire and application overview

The reviewed plots have inspired the visualizations deployed in the mobile application depicted in Fig. 4. These visualizations have been created by the authors of this manuscript on React Native using different available libraries, such as React Native SVG, React Native SVG Plots, React Native Plot Kit, D3.js, and React Native WebView. They are inspired from the conducted literature review, and from existing visualizations over the internet, especially from the galleries of the aforementioned libraries. After the first creation of the application, which included the visualizations, it was circulated among senior researchers and their feedback helped in enhancing the quality and design of both the charts and the application itself. One of the senior researchers have published papers related to data visualization for electrical energy consumption and browsing patterns in computer logs. Moreover, other senior researchers aided in questions' formulation by eliminating out-of-context questions, rephrasing the presented questions, and adding the analysis questions to quantify users' understanding of presented plots. Lastly, they provided their professional opinions on the represented data from their long teaching/research experience in academic institutes. The enhancements are carried out in a manner to reduce any possible bias incoming from the smartphones' operating system (OS). Thus, user feedback on such plots is crucial, where it is hoped that it catches their authentic experience and provides better judgement for which plots to be deployed at later stages. Although the first responses that the participants provide are only considered, the application still allows them to complete the questionnaire as much as they want without limiting their curiosity, and stores their extra responses for any possible use. This is depicted by the loop in Fig. 4. Participants are well-informed regarding the collected data on the first screen they face when the application is launched as shown in Fig. 4 "Home Screen".

To measure the participants' feedback, both qualitative and quantitative questions are addressed in the questionnaire. The qualitative questions are common for all plots to measure the participants' overall satisfaction regarding the plot they currently see, based on a five point Likert Scale. On the other hand, quantitative questions are tailored for each plot to measure the participants' understanding objectively. These measurements are adopted to deduce an accurate judgement of which plots to be deployed in the future.

This application is available for both iOS and Android. It has extremely similar behavior on both platforms as React Native framework is used to create this application. It is a cross-platform application development framework that allows developers to write a single program that will work on both iOS and Android operated smart devices. It is designed and debugged to work smoothly on smartphones with different screen sizes to avoid biasing participants with different screen sizes. A video showing the application can be found in the project's website which is included in our GitHub repository.[1]

Once the participant completes the questionnaire, his/her response is stored on Firebase online NoSQL database, namely Firestore. It offers cascaded filtering options which are deemed to be useful in analyzing the participants' responses (Sharma, 2018). Another reason is that libraries supporting Firestore database are well-established on numerous programming languages (i.e. JavaScript and Python). Database security is guaranteed using Firebase's Rules that prevent anyone from accessing database's content using any channel other than the smartphone.

4. Data visualization study

In this section, a discussion is carried over the achieved sample size, shedding light over important demographic features of the collected sample. Moreover, the visualization charts that are involved in the study are highlighted, detailing the information that are held within, mentioning explicitly how we utilized the publicly available dataset in our developed charts over the React Native mobile application.

4.1. Sample size

To conduct the visualization study, data are collated from a total of 133 participants from multiple countries. In terms of age, 58 and 55 out of the 133 participants are in 25–34 and 18–24 age range, respectively, constituting the largest portion. Conversely, 19 participants are in the 35–44 age group while only 1 participant represented the 45–54 age

[1] https://github.com/EM3-Project/EM3-Data-Visualization-Study-App.

Table 2
Study demographics.

Country	No.	Age Groups	No.
Qatar	81	25–34	58
Algeria	18	18–24	55
Greece	9	35–54	20
France	7		
United Kingdom	4		
United States	3		
Canada	2		
Jordan	2		
Switzerland	1		
Egypt	1		
Spain	1		
Germany	1		
Unknown	3		
Total Participants	**133**		

group. Naturally, 81 participants are from Qatar, representing the vast majority. Next in place is Algeria with 18 participants, followed by Greece (9), France (7), United Kingdom (4), United States (3), Canada (2), Jordan (2), Switzerland (1), Egypt (1), Spain (1), Germany (1), and 3 that could not be located. Among the 133 participants, 112 are males, and 21 are females. Table 2 numerates the study demographics.

It is noteworthy to know that the study has been distributed to graduate students and researchers in a number of universities and research centers including Qatar University, Harokopio University of Athens, and Algerian Center for Development of Advanced Technologies. This has also resulted in a male-majority because larger number of male students/researchers are targeted. Moreover, regarding the number of participants in each age band, it is clear that there is a sampling bias. Typically, the participation rate is skewed towards the younger demographic, which extensively use their smartphones, and have the time and ability to complete such questionnaires.

4.2. Employed data visualizations

The developed visualizations in this study, shown in Fig. 5, are split into two categories: conventional and enhanced. Conventional plots represent classical visualizations used for a plethora of applications. They are plain, simple, and easy to understand. They include bar, line, and stacked area charts. For the bar chart, it contains the energy consumption of the whole month aggregated in a single bar. It can be manipulated to show them aggregated on a weekly or even daily basis, but will create a long and hard-to-comprehend stream of bars, where the earliest/latest days will be harder to visualize. For the line chart, it is similar to the bar chart, however, the energy consumption data are connected to show a flow of energy consumption instead of single bars. For the stacked area chart, the target is to visualize the appliances consumption in an aggregated manner throughout the day, which is also capable of showing more appliances/rooms on the same chart. However, the main issue is that it will become incomprehensible if too many appliances are visualized together with no categorization. This visualization has been considered as conventional as its development has received a great attention in different applications (energy as in Koivunen-Niemi (2021), healthcare portrayed in Kusumawardani et al. (2016), etc.), especially with the wide use of the Python and R programming languages. Typically, various studies have been proposed to investigate a better design of interactive vertical (Talbot et al., 2014) and horizontal (Howorko et al., 2018) stacked bar charts.

On the other hand, enhanced visualizations convey information with richly-interactive plots that have multiple layers of meaning. They can potentially be harder to interpret, but can be quite valuable and succinct in presentation. Some enhanced plots are completely new data representations while others can be a mix of conventional plots. They include spiral, heatmap, and stacked bar interactive charts. Enhanced charts allow participants to interact with them in a way that the charts unravel more energy-consumption-related information once an interaction has been established. This feature could allow more understandability, establishing a deeper layer of meaning from the shown data. For the heatmap chart, it displays the energy consumption data for a single day in periods of 10 minutes. It is designed to be dynamic and compatible with different scenarios, where it can group the energy consumption data on hourly basis even. Once the user presses on any of the heatmap chart cells (periods), it shows the consumption of different rooms within a house as shown in Fig. 6. It can even show the energy consumption on the appliances level, instead of rooms, if the data are designed in such way. For the stacked bar chart with appliances, this chart can be considered as an enhancement to the stacked area chart. It is aimed at showing daily energy consumption, however, its novelty is that users can see each appliance's consumption and select which one to view for that day. Not only that, but if duplicates of the same appliance are available in the same household, such as lighting, television, etc., all will be stacked on top of each other in a dynamic behavior. For the spiral chart, it can be thought of as an enhanced version of the bar chart from the conventional group, but more concise, where the whole year, aggregated daily, can be easily visualized, and it incorporates the seasons in that year, with extra interactivity. For instance, if one of the bars is pressed, a tip is shown highlighting the date that specific bar represents, and the total amount of energy consumption in that day. Moreover, it shows the total consumption for all the past and present days, and the consumers can see their consumption in a specific day relative to other days, which makes it easier to visually understand the energy consumption without even looking into the consumption actual value.

What makes the enhanced charts an improvement to the conventional one is the following:

- They can be seen as an extended version of the conventional group, which to the best of our knowledge, are not implemented elsewhere in the fashion that we did, especially in the energy field sector.
- The interactivity these charts provide.
- Their concise representation of the visualized information, especially on small screens.
- Their creation on the React Native platform and presentation on small display devices.

As mentioned earlier, the majority of charts in Fig. 5 convey real energy consumption data that are taken from an existing open-source dataset. Both the bar and line charts show the energy consumption of year 2007 from IHEPCDS published by Hebrail and Berard (2012) aggregated on monthly periods. For the heatmap chart, the date 1-4-2007 is specifically chosen from the IHEPCDS dataset because it is the day with the highest variations within that year. The data are summed into 10-minutes periods to show the whole day's consumption. For the spiral chart, the energy consumption data recorded for the year 2007 in IHEPCDS are aggregated as days to show the consumption throughout the year. For the stacked area and stacked bar chart, the data are arbitrary, but are inspired from the Appliance Consumption Signature-Fribourg 2 (ACS-F2) dataset shared by Ridi et al. (2014).

5. Results and discussion

After the responses' collection phase, a Python script is developed to extract relevant statistics. For each of the plots, average scores for how effective is the plot in conveying the information, how easy it is to interact with, and how understandable its content is, i.e. effectiveness, aesthetic, and understandability, respectively, are calculated. Those metrics are used to determine the best visualization category, where the mean and the standard deviation (SD) of each metric are reported. SD is calculated by averaging the variances from each chart for a specific metric, and taking the square root of the resulting variance.

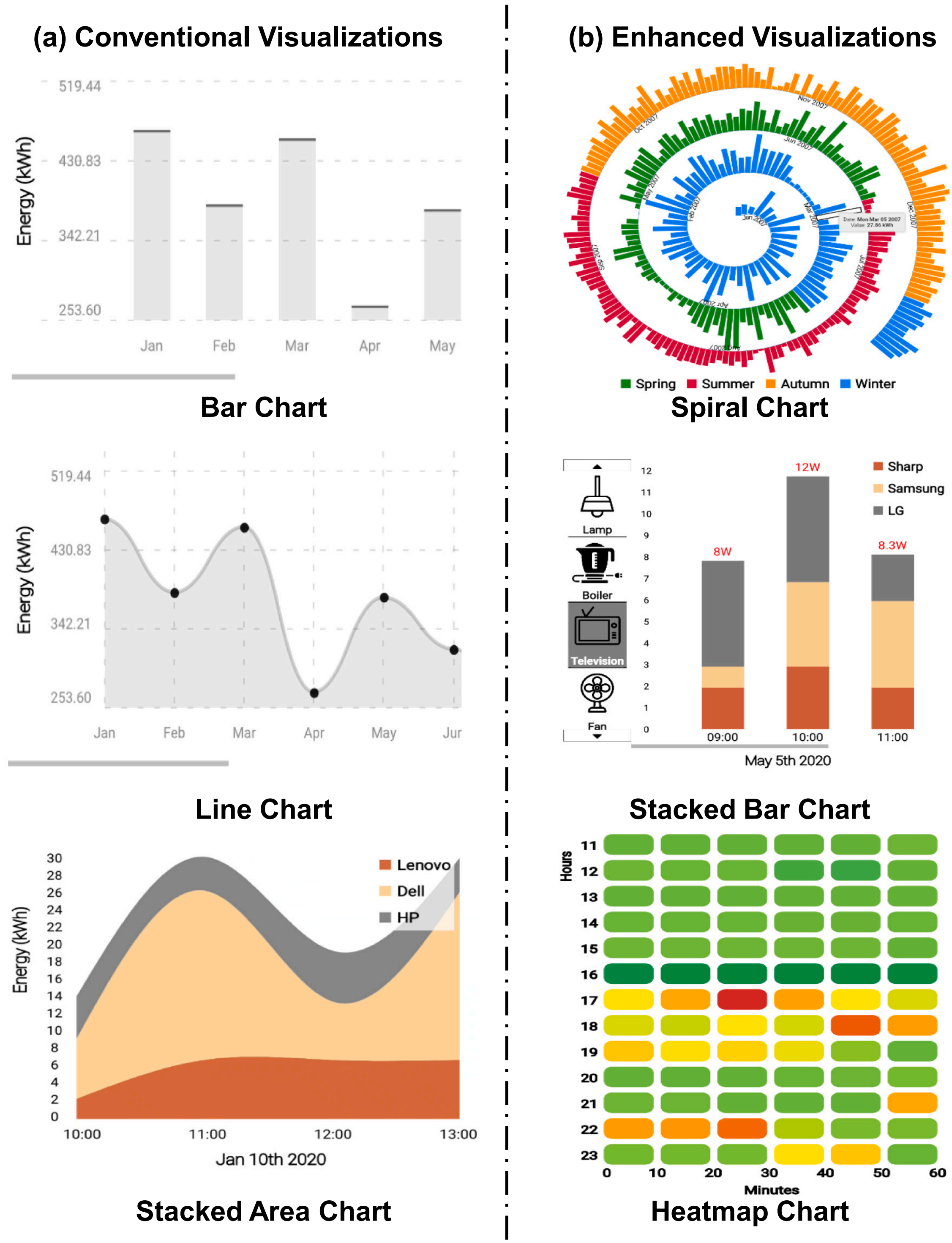

Fig. 5. Overview of (a) conventional and (b) enhanced study visualizations.

5.1. Enhanced vs. conventional

Fig. 7 illustrates the conventional and enhanced plots' results. Conventional plots scored an average of 4.255 (SD = 0.922) for understandability, 3.956 (SD = 1.048) for effectiveness, and 3.877 (SD = 1.046) for aesthetic. Note that to get these values for a specific chart group in a specific metric, you can simply take the mean of the three charts in that metric from Fig. 7. On average, and for the conventional group, bar chart had the highest scores, followed by the line and the stacked area charts, respectively.

Our null hypothesis states that there is no statistical difference (in terms of mean) between the conventional and enhanced groups over the three metrics, namely understandability, effectiveness, and aesthetics. In order to test the null hypothesis, we use the unpaired t-test on both enhanced and conventional groups. The picked threshold (α) is 0.05, allowing us to draw a conclusion with 95% confidence. The reason we use the unpaired t-test is that the study is conducted over

Table 3
T-test used parameters and relevant values.

Parameter	Understandability		Effectiveness		Aesthetic	
	Enhanced	Conventional	Enhanced	Conventional	Enhanced	Conventional
μ	3.467	4.255	3.487	3.956	3.508	3.877
σ	0.822	0.644	0.750	0.789	0.773	0.728
σ^2	0.676	0.415	0.563	0.623	0.598	0.530
N	65	68	65	68	65	68
df	121		131		130	
$t_{critical}$	2.428		2.425		2.425	
$t_{estimated}$	6.135		3.511		2.837	

Where μ is the mean, σ is the SD, σ^2 is the variance, N is the sample size, df is the degree of freedom for the t-test, $t_{critical}$ is the critical t value for two-tailed test with $\alpha_{new} = \frac{0.05}{3}$, and $t_{estimated}$ is the estimated t value from the unpaired t-test.

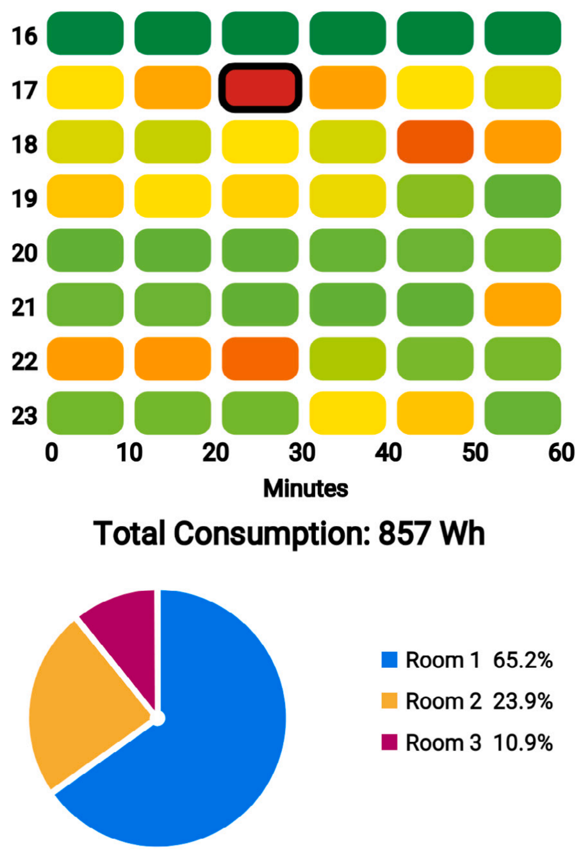

Fig. 6. Detailed view of the heatmap when tapping on a cell.

two independent samples, and the aim is to compare the mean of the sample's ratings to the group they are assigned. Moreover, parametric tests are more powerful than non-parametric tests, and the unpaired t-test can be applied on the case of our study because we have a minimum sample size of 65 (65 participants for the enhanced group, while 68 for the conventional group). For the unpaired t-test, the relevant parameters are mentioned in Table 3. Because we are using three variables simultaneously for comparison, we use the Bonferroni correction term, which in essence instructs us to divide α by the number of t-tests applied simultaneously. Because the number of t-tests is 3, Bonferroni correction term generates a new α that can be utilized to get $t_{critical}$. α_{new} is calculated as following:

$$\alpha_{new} = \frac{\alpha}{3} \rightarrow \alpha_{new} = 0.01667 \tag{1}$$

where α is the probability that the population parameter will not be in the confidence interval, and α_{new} is the corrected version of α by the Bonferroni correction term.

It is worth noting that the SD used in the t-test is calculated from the averaged ratings, while the previous SDs are calculated from the variances of the original ratings. The reason for using such SDs for the unpaired t-test is to be consistent with the number of samples for each group. If we use the previous SDs, it will be as if we are taking into account the sample size multiplied by 3 for each group. From Table 3, it is clear that the inter-group difference is evidently high given that $t_{estimated} > t_{critical}$ for all three metrics with $\alpha_{new} = \frac{0.05}{3}$. Thus, from this multivariate unpaired t-test, we reject the null hypothesis of having both groups equally favored by participants. We can confidently (95% confidence interval) say that the conventional plots are favored by the participants.

From the aforementioned results, it is evident that there is discrepancy between the average scores of conventional and enhanced visualizations. Conventional plots excel by 22.74% in understandability, 13.44% in effectiveness, and 10.54% in aesthetic. This could be explained by the fact that conventional plots are considered more familiar. Moreover, the plain and simple nature of these visualizations can simplify participants' understanding and interaction with them. On average conventional plots scored higher in terms of effectiveness, aesthetic, and understandability but slightly lack in terms of content analysis. Enhanced plots generated a higher percentage by 8% in the analysis questions' responses compared to the conventional counterparts, perhaps due to the fact that participants needed longer time to grasp the portrayed enhanced plots and paid more attention to the details within. This could have led them to learn more about the plots and the information they present.

This conclusion produces several insights. Enhanced plots can be used to convey energy consumption data as effective as conventional visualizations but with higher levels of meaning, extra interactivity, and more importantly, flexibility towards varying datasets (e.g. appliance level or aggregated). However, they are not favored by the participants as they can be complex for unfamiliar end users. Also, classical plots can be used all the same when the dataset employed is simple. Moreover, anonymous participants' location data aid in providing richer understanding of the study data. As an example, anonymous location data can provide insight on how certain demographics can perceive energy data visualizations differently.

5.2. Comparison with the state-of-the-art

Even though a significant interest has been paid recently to energy data visualizations, it is still a difficult task to compare visualizations or conduct related surveys/questionnaires and rigorously understand the state-of-the-art. Specifically, different parameters essentially impede results reproducibility and restrain empirical comparison of existing visualization plots and executed surveys/questionnaires. They can be summarized as follows: (i) it is very challenging to assess the generality of energy data visualizations as most visualization tools are implemented for distinct scenarios and use different data types. Moreover, researchers also often clean, pre-process, and resample energy

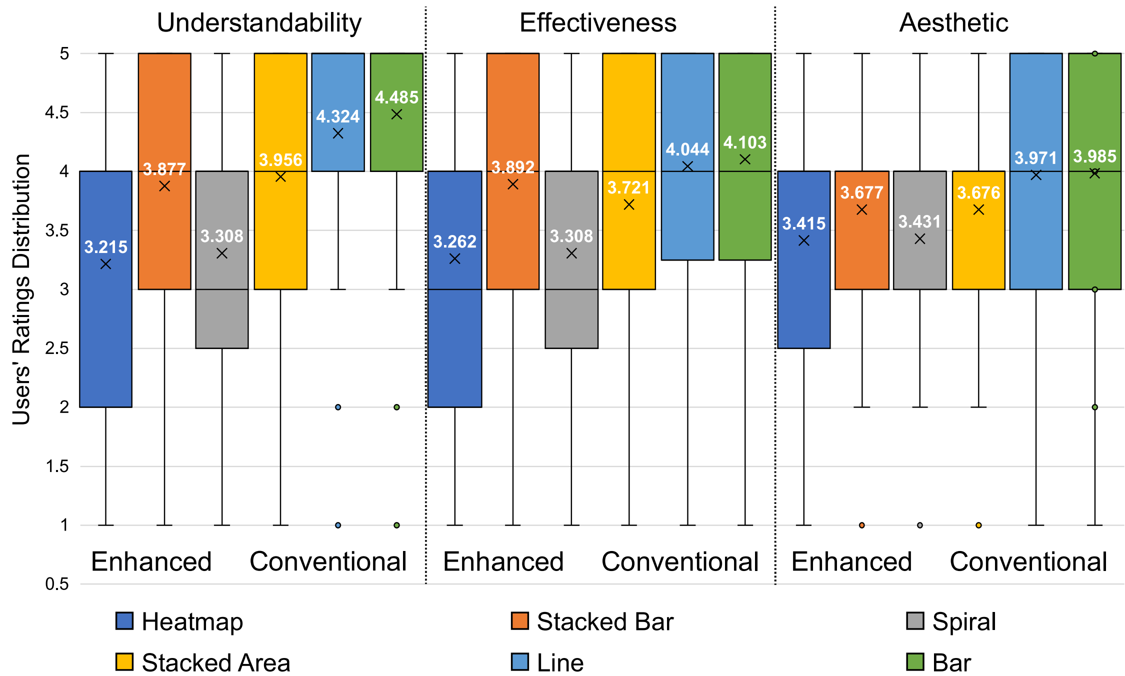

Fig. 7. Conventional and enhanced visualizations' results.

consumption footprints based on their specific needs, where appliance-level or aggregated-level are considered in our work. Consequently, this makes empirical reproduction of the visualization plots difficult; (ii) there is an absence of questionnaire comparisons using the same benchmarks, which is principally due to the lack of available open-source benchmark toolkits, and the use of different population samples in different regions; and (iii) it is worthy to mention that to the best of the authors' knowledge, this is the first work that develops a React Native application as a questionnaire to assess the efficacy of several energy data visualizations in an interactive way.

However, our study can be compared with other questionnaire/survey studies on other relevant aspects such as the number of individuals participating in the study, number of countries involved, the type of consumption data used, and the nature of the deployed tool. Table 4 illustrates a comparison between the proposed study and the state-of-the-art in terms of the aforementioned parameters. It is clearly seen that the proposed questionnaire has various advantages. For example, the number of participants in our study reached 133, which is much higher compared to those published by Costanza et al. (2012), Herrmann et al. (2017), who used feedback from 15 and 43 participants, respectively. Furthermore, in our case, the participants are from multiple countries, while for all the other studies, they are only from a unique country or even from the same region, which limits the validity and applicability of their outputs to only a particular country or region. Therefore, to the best of our knowledge, we introduced the most comprehensive energy data visualization questionnaire in this article. Moreover, it is worth noting that the questionnaire has been sent to more than 200 individuals; however, we have got 133 responses. On another side, the study's objective was to check the ability of end-users to reply to this kind of questionnaire. Consequently, to not bias the analysis, we have considered only the received responses of the 133 participants without insisting on the other participants to send their responses.

In addition, we have deployed the questionnaire study using a mobile application because individuals are actually empowered by smartphones each day, where if such devices are utilized correctly, they can be a productivity-boosting instruments. Therefore, making research questionnaires/surveys using mobile applications is now a challenging task, which facilitates and motivates individuals to participate in such studies. In contrast, other studies used traditional techniques based on websites or web applications. Indeed, mobile applications provide more benefits compared to websites or web applications: (i) they are faster than web-based tools; (ii) they can offer more functionalities because they have access to the system's resources; (iii) they can work offline; (iv) they provide great security and safety options (since native applications should first be approved by the App Store); and (iv) they are easy to build because of the availability of developer tools, interface elements, and software development kits (SDKs).

6. Conclusion

In this paper, a data visualization study on domestic energy data is conducted. Conventional visualizations, namely bar, line, and stacked area charts, are compared against enhanced charts, namely spiral, heatmap, and stacked bar charts, in terms of effectiveness, aesthetic, and understandability. The study is conducted through a mobile application circulated to participants in multiple countries. From the 133 responses, conventional data visualizations can be considered superior in terms of effectiveness, aesthetic, and understandability against the enhanced plots, however, lacking when it comes to the analysis questions. From the received responses, conventional plots outperformed enhanced plots by 22.74% in understandability, by 13.44% in effectiveness, and by 10.54% in aesthetic. Enhanced plots, on the other hand, generated higher correct analysis questions' responses by 8%. From the 133 collected responses, and after applying the multivariate unpaired t-test, conventional energy data visualization plots are considered superior in terms of understandability, effectiveness, and aesthetic.

The conducted study has several limitations. First, the scope of the study could be larger to span more regions and wider representative demographics, with more focus on reducing the gap between the male and female participants' genders. This will help in increasing the credibility of the results. Second, more powerful statistical tools could be employed for thorough analysis of study data. Part of our next steps in this work is to develop a real-time interactive tool that can help end users to visualize actual energy consumption footprints collected at aggregated or appliance-levels, coming from the data collection module. Moreover, it allows interaction with the connected appliances, especially if an anomalous consumption is observed such as excessive consumption, or consumption while end user is outside.

Table 4
Comparison of proposed study with state-of-the-art.

Study	# Participants	Utilized Tool	Data Level	# Participants' Countries
Herrmann et al. (2017)	43	Online questionnaire	Appliance	1
Watanabe et al. (2013)	–	Web application	Appliance	1
Costanza et al. (2012)	15	Online questionnaire	Aggregated	1
Proposed Work	**133**	**Mobile application**	**Appliance & aggregated**	**12**

CRediT authorship contribution statement

Ayman Al-Kababji: Conceptualization, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Abdullah Alsalemi:** Conceptualization, Methodology, Software, Writing – original draft, Visualization. **Yassine Himeur:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Rachael Fernandez:** Conceptualization, Methodology, Software, Investigation, Writing – original draft, Writing – review & editing. **Faycal Bensaali:** Conceptualization, Validation, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Abbes Amira:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Noora Fetais:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.132841.

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